ABSTRACT

Title of thesis: ELUCIDATING RECRUITMENT STRESSORS FOR THE MARYLAND STATE ENDANGERED COMMON TERN (*Sterna hirundo*) THROUGH USE OF A MINIMALLY INVASIVE SURVEILLANCE SYSTEM

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In this thesis, I monitored two breeding colonies of the Maryland state endangered common tern (*Sterna hirundo*) using a surveillance system composed of video cameras and temperature loggers. This system was coupled with an in-depth image analysis of Landsat scenes to quantify island loss in the Chesapeake Bay and coastal bays of Maryland and Virginia from 1986 to 2016. Incubation duration was determined through analysis of both in-nest temperature and video footage. Incubation trends varied between colonies but an overall trend of nighttime desertion was observed on Skimmer Island as a result of predator presence. Island loss was documented in the region since 1986. Area of beach habitat, key for breeding populations of this species, increased in 1996 and 2011 as a result of sand accretion on coastal islands and the construction of Poplar Island. All other habitat types declined. This thesis is the first to document island loss in the Chesapeake Bay beyond 2011 and the first to quantify the impact of Poplar Island's construction on the region. To promote future breeding of common terns in Maryland, resources must be allocated to

create new habitat islands removed from the mainland and free of nesting predators. Existing islands must also be supplemented yearly with substrate to mitigate erosion from sea level rise.

ELUCIDATING RECRUITMENT STRESSORS FOR THE MARYLAND STATE ENDANGERED COMMON TERN (*Sterna hirundo*) THROUGH USE OF A MINIMALLY INVASIVE SURVEILLANCE SYSTEM

by

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INTRODUCTION

The common tern (*Sterna hirundo*) (hereafter COTE) is one of the most widespread waterbird species with a mainly Holarctic breeding distribution and tropical wintering distribution. Populations of COTE have fluctuated for centuries with the species being nearly driven to extinction on the Atlantic seaboard in the late 1800s due to extensive harvesting for the millinery trade (Nisbet et al., 2017). Due to the passage of the Migratory Bird Treaty Act in 1918, the species saw a comeback and by the 1930s, COTE had regained much of its original range and the population nearly reached pre-harvesting numbers. Since then, breeding numbers of COTE have been in a steady decline throughout North America due to various disturbances at the breeding colonies and as a result, the species has been the focus of extensive conservation efforts in recent years (Nisbet et al., 2017). Due to these disturbances, COTE were listed as a Maryland state endangered species in August 2016 (Maryland Natural Heritage Program, 2016).

In Maryland, the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island (hereafter Poplar Island) (Figure 1A) is the only known nesting site of COTE in the Chesapeake Bay aside from an unconfirmed ephemeral colony located on a dredging barge in the Patapsco River near Baltimore, Maryland. The only other known breeding colony for the species in Maryland is outside of Ocean City, along the Atlantic seaboard in the Isle of Wight Bay. Extensive monitoring of the species by the U.S. Fish and Wildlife Service (USFWS) and USGS Patuxent Wildlife Research Center has taken place at Poplar Island

since the late 1990s. The Maryland Department of Natural Resources (MD DNR) and the Maryland Coastal Bays Program have monitored the Ocean City colony since the mid-1990s as well. Waterbird breeding colonies on Poplar Island (snowy egrets (*Egretta thula*), cattle egrets (*Bubulcus ibis*), black-crowned night heron (*Nycticorax nycticorax*), and tricolored herons (*Egretta tricolor*) have all been documented nesting here) have been monitored since the 1990s with COTE and least tern (*Sternula antillarum*) monitoring beginning in 1998.

Skimmer Island, a collection of small islands in the Isle of Wight Bay, has been a critical nesting site for black skimmer (*Rynchops niger*), royal tern (*Thalasseus maximus*), and COTE since the mid-1990s (MD DNR, 2016). The main breeding colonies for COTE in the Isle of Wight Bay are OC Spoils and Skimmer Island, both part of the collective Skimmer Island (Figure 1B). Storms and high water levels have led to the continued erosion of Skimmer Island since the late 1990s. A partnership was formed in 2009 between the Ocean City Fishing Center, the Maryland Coastal Bays Program, and the Maryland Department of Natural Resources to combat this rapid habitat loss through the addition of clean sand dredged from the Fishing Center's approach channel (MD DNR, 2016). Sand has been added to Skimmer Island every March since to improve nesting conditions for the species during the upcoming nesting season. As the sea level continues to rise, more sand will be added as needed in order to continually promote high quality nesting habitat in the Isle of Wight Bay.

Documented threats to COTE throughout its range include habitat degradation from development and recreational activities (Erwin, 1980), disturbance at nesting and roosting sites (Nisbet et al., 2017), and displacement and predation by a number of species (primarily herring (*Larus argentatus*) and great black backed gulls (*L. marinus*), great horned owl (*Bubo virginianus*), and red fox (*Vulpes vulpes*)) (Kress 1983, 1997; Burger and Gochfeld, 1991). Determining the main threats to this species in Maryland and what has primarily caused a decline in population numbers and hatching success is paramount for future research and management of COTE throughout the state and elsewhere in its native range.

Habitat destruction and human disturbance

In the Mid-Atlantic region during the late 1970s, oceanfront development forced terns and other colonial waterbirds to nest on dredge spoil islands instead of on open beaches like they had in the early 20th century (Erwin, 1980). An increase in development forced humans closer to the breeding colonies therefore requiring COTE to seek nesting habitat elsewhere. As Erwin (1980) documented in Virginia, the majority of waterbird colonies were located on pristine beaches on the barrier islands along the eastern shore of the state (81%). Meanwhile, in New Jersey, where heavy oceanfront development was occurring, less than 10% of waterbird populations bred on traditional sandy beaches. At the same time, shoreline development and human encroachment on breeding habitat were greatly increasing throughout the entirety of the Chesapeake Bay region. As a result of this increased disturbance, waterbird populations in the Bay have declined significantly (Erwin & Beck, 2007). Studies have shown that beach erosion and development may have had a

considerable effect on COTE populations throughout the Chesapeake Bay and coastal bays (Erwin, 1980; Brinker et al., 2007; Erwin et al., 2011). Development has been particularly pronounced in Ocean City, Maryland, a city with a year-round population of 7,089 and a summer population upwards of 300,000 (Robbins & Houston, 2006, U.S. Census Bureau, 2014;). This influx of population during the breeding season has forced COTE to nest and breed away from the beaches, and has also forced them to nest on islands in the coastal bays which may be more prone to flooding and wake erosion.

Sea level rise may ultimately become the most difficult to manage and predict of all major threats affecting breeding colonies of COTE and other colonial nesting waterbird species. The rate of sea level rise is expected to be greater than 50-cm by the end of the 21st century but it is predicted that the rate will be even greater along the Mid-Atlantic coast (Erwin et al., 2006; IPCC, 2007; Church et al., 2013). Many small islands that were once breeding colony sites (as indicated in a region wide breeding population survey of waterbirds along the Atlantic Coast) have completely eroded away as a result of increased sea levels (Erwin & Korschgen, 1979; Brinker et al., 2007). Inundation of wetlands and coastal island loss as a result of increasing sea levels is highly likely throughout several counties in Maryland (Dorchester, Somerset, and Worcester) and Virginia (Accomack and Northampton) on the Delmarva Peninsula (Titus & Richman, 2001). The stabilization of the Ocean City Inlet, which was originally conceived to dampen the impacts of sea level rise, has reduced the frequency of storm water-related breaches at both Assateague Island in Maryland and Fenwick Island in Delaware. These breaches had once created tidal islands that were important nesting sites for waterbirds in the region. With the construction of the Inlet

stabilization, this natural process no longer occurred and in turn, this critical nesting habitat was never formed (USACE, 1998; Brinker et al., 2007). A large majority of breeding waterbird species in the Chesapeake Bay region (90%) actively nest on land below 1.5 m in elevation, land which is at elevated risk for coastal inundation in the near future (Erwin et al., 2006). Even though the exact rate of sea level rise is difficult to predict, the consequences of any significant change in sea level can be catastrophic to nesting waterbirds throughout the region.

Human disturbances at the breeding site can be particularly detrimental to the species. Disturbances there may hinder breeding site occupation and increase the amount of nest desertion which may lead to chick or egg death from overheating or chilling (Carney & Sydeman 1999; Nisbet et al., 2017). The harmfulness these disturbances have on a breeding colony is dependent on three factors: 1.) the type, frequency, and duration of the disturbance, 2.) weather and/or presence of predators nearby, and 3.) the behavioral response of the nesting birds to a disturbance (Gochfeld, 1981). The more severe, frequent, and long lasting the disturbance is, the greater the repercussions. Some major impacts that human disturbance has on colonial waterbird colonies include egg and nestling mortality, premature fledging or nest abandonment, and reduced body mass and lower growth rate of chicks (Rodgers & Smith, 1995). For COTE, adults leave the nest to distract the threat away from their nests (Nisbet et al., 2017). This temporary nest abandonment leaves eggs and chicks exposed to both adverse weather and predation events thus negatively affecting overall reproductive success.

Carney and Sydeman (1999) state that colonial nesting waterbirds like COTE are particularly prone to human disturbances due to the colony's high visibility and visually stunning feeding and nesting behaviors which attract humans to the colonies. It has been shown by various studies that the reproductive success of terns decreases with high levels of investigator disturbance at the breeding colonies (Brubeck et al., 1981; Gochfeld, 1981; Nisbet, 1981). These high levels of disturbance are typically associated with nest monitoring activities. Following this disturbance, nests were lost through abandonment, intraspecific aggression within the colony, or inter-/intraspecific nest predation (Carney & Sydeman, 1999). Non-investigator disturbance also negatively affects breeding success of tern colonies (Erwin, 1980; Burger et al., 1995; Burger, 1998). Erwin (1980) found that recreational disturbances decreased both tern and gull nesting success on barrier beaches in New Jersey. Likewise, tern colonies exposed to ecotourism activities in New Jersey were smaller and had lower reproductive success than other colonies (Burger et al., 1995). Burger (1998) also found that COTE were sensitive to motor boats and personal watercrafts near the colonies. The highest number of individuals fled the colony during close or high-speed approaches. This is of particular importance at Skimmer Island where heavy boat traffic is commonplace in the summer. The inception of the no wake zone near the island has decreased overall noise levels and this may ultimately be beneficial for the species in the future.

Environmental contaminants

The effects of manmade chemicals, primarily pesticides such as DDT/DDE and industrial plastics like PCBs, and heavy metal contamination in water, on various avian species have

been extensively documented for decades. These effects were most notably documented in Rachel Carson's 1962 magnum opus "Silent Spring". Since the 1970s, researchers have observed these manmade chemicals negatively affecting waterbird breeding biology as well (Hays & Risebrough, 1972; Fox, 1974, 1976). Throughout their breeding range, COTE breeding success was reduced in part due to these harmful chemicals leaching into the water supply and becoming bioaccumulated within prey fish species (Nisbet et al., 2017). PCBs and DDE are the main organochlorine residues found in COTE since the mid-1960s (French et al., 2001; Nisbet et al., 2017). Some effects of environmental contamination in COTE include eggshell thinning (Fox, 1974, 1976), congenital deformities (Hays & Risebrough, 1972; Gochfeld, 1975; Gilbertson et al., 1991), and reproductive failures (Fimreite et al., 1971).

DDE, also known as dichlorodiphenyldichloroethylene, is a pesticide once used to protect crops and eliminate disease carrying insects in the United States until its production was banned in 1973. Today, the chemical may be found in the environment as a result of previous contamination or as a product in the breakdown of DDT (dichlorodiphenyltrichloroethane), another manmade pesticide used extensively in the 1950s and 1960s in North America (USEPA, 2008). DDE is insoluble in water and may easily enter surface waters through runoff containing contaminated soil particles. This compound is subject to both photo- and biodegradation as well as volatilization, all of which make this compound particularly deadly once found in the water supply (USEPA, 2008).

Use of DDE across the United States in the 1950s and 1960s led to sharp declines in COTE breeding population numbers and overall breeding success (Nisbet et al., 2017). Levels of DDE at COTE colonies in Maryland have steadily declined since the 1970s from 0.30-0.78 ppm between 1977 and 1984 (Switzer et al., 1973) to <0.06 ppm between 1988 and 1998 (Vermeer & Reynolds, 1970). COTE are highly sensitive to the presence of this compound in the water supply with severe effects on breeding success observed at colony wide levels as low as 4.0-4.4 ppm (Fox, 1976; Nisbet & Fox, 2009) with some hatching failures occurring as low as 1.9 ppm (Nisbet & Reynolds, 1984). From 1968 to 1973, low hatching success and productivity in several colonies in Alberta, Canada and the Great Lakes region of the United States were associated with defective, poorly developed eggshells as a result of DDE contamination at the colony level. In general, DDE contamination of COTE breeding colonies may impact proper development of eggshell composition and structure, reduce gas exchange between a developing chick and the surrounding environment, and lead to egg breakage (Fox, 1974; 1976; Nisbet et al., 2017).

PCBs, or polychlorinated biphenyls, are manmade organic compounds manufactured between 1929 and 1979 which were used in hundreds of industrial and commercial applications ranging from plasticizers in paints to cable insulation to floor finish (USEPA, 2018). These chemicals may be released into the environment through improper disposal of contaminated waste, leaks or releases of contaminated water from electrical transformers, or burning of some waste. Once released, PCBs do not readily breakdown and often have extended half-lives leading to prolonged environmental contamination

which may last for decades (USEPA, 2018). PCBs found in water may accumulate in fish which, when ingested, bioaccumulate and cause varying detrimental effects.

COTE are particularly susceptible to the "dioxin-like" toxic effects of PCBs including embryotoxicity and congenital deformities (Hoffman et al., 1998). In the early 1970s, deformities were frequently documented at several coastal and inland sites throughout North America (Hays & Risebrough, 1972; Gochfeld, 1975; Gilbertson et al., 1991) but negative effects have been documented as recently as 2007 (Jablonski, 2009; Ward et al., 2010). Much like DDE levels, Maryland PCB levels have declined steadily since the 1970s from 0.7-2.2 ppm between 1977 and 1984 (Switzer et al., 1973) to <0.06 ppm between 1988 and 1998 (Vermeer & Reynolds, 1970). In 1984, colonies in Saginaw Bay, MI with documented PCB levels of 10-11 ppm experienced low hatching success and abnormal embryo development as compared to control colonies with lower PCB levels of 4-7 ppm (Hoffman et al., 1993). At several colonies in North Chicago, IL from 2005 to 2007, mean PCB concentrations of 12 ppm were observed which caused low reproductive success and deformities in COTE chicks (Jablonski, 2009; Ward et al., 2010). It is important to note, however, that DDE concentration was not measured in these colonies.

Heavy metal contamination has plagued waterways throughout the industrialized world for centuries. Organisms that live in or near these waters may bioaccumulate these harmful elements and cause detrimental effects to themselves and those who prey upon them. Various metals have been found in COTE tissues and eggs through environmental contamination including mercury, lead, cadmium, chromium, selenium, and arsenic

(Nisbet et al., 2017). High mercury levels in eggs and tissues of COTE were reported in 1970s and 1980s at many colonies along the Atlantic coast of the United States (Burger & Gochfeld 1988; 2016). These elevated levels were associated with reproductive failures at colonies situated downstream of industrial sources in Ontario, Canada and Michigan between 1969 and 1971 (Fimreite et al., 1971). The highest ever recorded level of mercury contamination in COTE feathers was 12 ppm at Bird Island, MA in 1991 (Burger et al., 1992). A stable isotope analysis revealed that these extreme levels resulted from adults feeding on prey at low trophic levels (Nisbet et al., 2002).

Elevated levels of iron, cadmium, chromium and selenium were found in COTE eggs, feathers and tissues in New Jersey, New York, Rhode Island, and Massachusetts in the 1970s and 1980s (Burger & Gochfeld 1988; 2016). In 1971, dangerously high levels of iron and cadmium (9 ppm and 1.4 ppm, respectively) were found in COTE eggs at a colony in Barnegat Bay, NJ (Burger et al., 1994). Researchers believed these elevated levels were caused by the proliferation in the use of leaded gasoline in the United States. These lead levels fell well within the range associated with feather loss in wild adults as well as adverse effects on adult behavior and chick growth in laboratory grown individuals (Burger et al., 1994). The cadmium levels also were within the range of inflicting various adverse effects on adults (Burger & Gochfeld, 2016). Both of these levels declined steadily since to < 1 ppm and < 0.01 ppm, respectively (Burger et al., 1994). Increased levels of chromium were found to cause biochemical changes within COTE chicks at a contaminated nesting colony in Providence, RI. No effects of chromium contamination on chick survival rates have been reported (Custer et al., 1986). Levels of both chromium and selenium were found to

increase with age whereas levels of iron, cadmium, and lead did not since these metals are likely excreted in feathers at each molt stage (Braune, 1987). COTE molts are therefore considered an important detoxification mechanism.

Nest predation

Due to their ground nesting habits, COTE are particularly prone to predation at the breeding colony. A total of over 30 avian, 13 mammalian, and a number of reptilian and invertebrate predators have been documented predating on COTE in North America (Nisbet et al., 2017). The most common nest predators include herring gulls (*Larus aregentatus*) (hereafter HERG), great-black backed gulls (*Larus marinus*) (hereafter GBBG), ring-billed gulls (*Larus delawarensis*) (hereafter RBGU), black-crowned night heron (*Nycticorax nycticorax*) (hereafter BCNH), great horned owl (*Bubo virginianus*) (hereafter GHOW), red fox (*Vulpes vulpes*), and raccoon (*Procyon lotor*) (Hunter & Morris, 1976; Morris & Wiggins, 1986; Burger & Gochfeld, 1991; Shealer & Kress, 1991; Blokpoel et al., 1997; O'Connell & Beck, 2003; Nisbet et al., 2017).

Several species of *Larus* gulls experienced an abundant increase in numbers in the Western Hemisphere over the past several decades due to high growth in the production of urban waste and fisheries discards (Camphuysen, 1995; Pons & Migot, 1995; Guillemette & Brousseau, 2001). These species typically have a generalist diet but some individuals may develop highly specialized and predatory food habits (Southern & Southern, 1984; Guillemette & Brousseau, 2001). These individuals represent roughly 1% of the nesting population, they are often highly territorial, and the majority are males (Guillemette &

Brousseau, 2001). A study conducted in the Gaspe Peninsula of Quebec, Canada found that COTE reproductive success was greatly reduced by predatory gulls. The researchers surmised that a single individual was predating a majority of the hatched chicks (Guillemette, 1993).

Larger gulls (e.g. RBGU) typically affect COTE breeding quality by arriving early at the colony sites and nesting in traditional COTE habitat (sandy islands/peninsulas with little vegetative cover (10-30%) near a reliable food supply) thus displacing COTE and forcing the species to nest in suboptimal habitat (Courtney & Blokpoel, 1983; Blokpoel et al., 1997). One such example was highlighted in Courtney and Blokpoel (1983). The authors mention that competition for nesting sites between COTE and RBGU on the Great Lakes was particularly severe due to an increase in the RBGU population and little available nesting habitat in the region, near-complete overlap of preferred nesting habitat between these species, and the early annual arrival of RBGU to the region (roughly 2-4 weeks earlier than COTE). RBGU also use suboptimal COTE nesting habitat with high vegetation which thus further constricts the available nesting habitat for COTE. Courtney (1979) mentions that, while egg predation is rare, RBGU was the main avian egg predator in this region.

HERG and GBBG are other well-known nesting predators of COTE (Hatch, 1970; Courtney & Blokpoel, 1983; Becker, 1995; O'Connell & Beck, 2003). As mentioned in O'Connell and Beck (2003), both species have had range expansions southward since the 1950s and began breeding in the Mid-Atlantic region at that time. With this expansion, a new threat to nesting waterbird populations developed. It has been suggested that as gulls

expand their range, tern colonies at the leading edge will experience a swift increase in gull nesting predation (Burger & Lesser, 1976; O'Connell & Beck, 2003). COTE breeding population numbers have declined on the Virginia barrier islands as a direct result of this southward expansion (Williams et al., 1990). In fact, the number of breeding pairs of gulls on the Virginia barrier islands has greatly increased since the 1960s. Recently, this population was very close to the total estimated number of breeding pairs of COTE, least terns (*Sternula antillarum*), gull-billed terns (*Gelochelidon nilotica*), and black skimmers (*Rynchops niger*) on those islands (6000 vs. 7000 individuals) (Watts & Byrd, 1998; O'Connell & Beck, 2003;).

While both gull species may cohabitate with COTE on a larger island like Poplar, this is often not the case as gulls will occasionally feed on chicks, and, more rarely, eggs of COTE. If many COTE adults begin mobbing a gull, the chick will be carried away from the colony and consumed there (Hatch, 1970). At colonies along the Atlantic coast of Virginia, gull predation of chicks greatly decreased overall hatching success. Some colonies had hatching success numbers as low as 1.8% as a result (O'Connell & Beck, 2003). In the presence of gulls, COTE will nest away from these species to avoid predation at the nest. COTE will only actively nest nearby breeding HERG and GBBG if the nesting colony has faced high predation pressures from gulls or mammalian predators. In areas highly influenced by tides, gulls tend to nest above the storm tide line and this may further force COTE to nest in close proximity to nesting gulls in order to avoid washout of nests (O'Connell & Beck, 2003). In contrast, it was also suggested by O'Connell and Beck (2003) that the presence of both gull species at or near the breeding colonies may have pushed terns to areas that are more

prone to frequent tidal flooding. This may be the case for COTE at Ocean City where both gull species are present nearby Skimmer Island.

Other known predators of COTE are BCNH, GHOW) and red fox (*Vulpes vulpes*) (Nisbet et al., 2017). Both GHOW and red fox actively prey on adults, eggs, and chicks. Often when one of these predators is encountered in a breeding colony, the entire colony may be at risk. Because red foxes often cache their prey, they are capable of removing more individuals from a breeding colony than they could consume during a single visit (Nisbet et al., 2017). Both COTE and HERG have been known to abandon entire islands once red foxes are present (Burger & Gochfeld, 1991). In 2015, predation pressure by red fox on Poplar Island caused COTE to renest multiple times in the same location unsuccessfully before eventually moving elsewhere on the island (Prosser, 2015). Least terns (*Sternula antillarum*) (LETE) attempted to renest fewer times than COTE before ultimately abandoning their colonies (Prosser, 2015).

BCNH primarily prey upon pipped eggs and small chicks of COTE (Hunter & Morris, 1976; Shealer & Kress, 1991). Evidence suggests that much like gulls, individual BCNH may specialize as tern predators (Hall & Kress, 2008). Presence of this species at the colony may lead to nocturnal nest abandonment by COTE adults (Shealer & Kress, 1991). As stated previously, this nest abandonment negatively affects breeding success. On Stratton Island, Maine, fledging success was extremely low (0.24 chicks/pair) as a result of BCNH presence (Shealer & Kress, 1991). In one colony, BCNH were observed hunting primarily by sound, which was indicated by individuals walking slowly through the colony, stopping

frequently, keeping their head stationary, and then slowly walking in the direction of the nest (Hunter & Morris, 1976). This hunting behavior supports why pipping eggs and young chicks, with their near constant calling, were the prey of choice for BCNH.

GHOW predation is characterized by decapitated adults and chicks and partially eaten bodies. This species and the related short eared owl (*Asio flammeus*) prey on adults until they are no longer available and when this occurs, they begin preying on both young and old chicks (Nisbet & Cohen, 1975; Holt, 1994; Arnold et al., 2006). GHOW has been an important predator for nesting terns in New England since the early 1900s but is not considered a major nesting predator in the mid-Atlantic region (Nisbet, 1975; Burger & Gochfeld, 1991). GHOW were detected on Poplar Island in 2013 and have nested on nearby Coaches Island for several years (Prosser, 2015). In response to GHOW presence, COTE may desert the colony at night for upwards of 8 hours, thus exposing both chicks and incubating eggs to detrimental weather conditions (Nisbet et al., 2017). Demographic failure on Poplar Island is currently thought to be attributable to failure in the egg stage due to extended exposure and subsequent predation or incomplete embryo development (Prosser, 2015).

Since 2013, game cameras have been placed in COTE colonies on Poplar Island in an effort to identify nest predators. Species captured by the game cameras include GHOW, red fox, red-winged blackbirds (*Agelaius phoeniceus*), Canada geese (*Branta canadensis*), white-tailed deer (*Odocoileus virginianus*) and nutria (*Myocastor coypus*). Not all of these species

are known predators of COTE (nutria, Canada goose, and white-tailed deer), but their presence may have some impact on the species.

Nest attentiveness and food resources

Nest attentiveness is defined as the time at least one adult is present on a nest (Nisbet et al., 2017). This can be affected by food availability (Martin, 1987), presence of predators (Burger & Gochfeld, 1991; Meehan & Nisbet, 2002), or high temperatures (Nisbet et al., 2017). The availability of food, or lack thereof, leads to a negative relationship between incubation and foraging in which adults must balance foraging for themselves with incubating their eggs (Martin, 1987). The more time adults spend incubating eggs, the shorter overall time required before the eggs can hatch. However, the more time spent on the eggs, the less foraging time they have. The one benefit to this shorter incubation time is that the probability of predation on eggs and adults decreases as nest attentiveness increases. One study found that, on average, foraging trips by COTE adults to feed their young was 17.2 minutes (min) long and that an estimated 42 to 64% of daylight hours (h) (between 7 and 10 h total) were spent foraging (Courtney & Blokpoel, 1979). The jump in percentages correlated with an increase in the brood size from one to four chicks. With this extended amount of time away from the nest, both eggs and chicks are more exposed to predators and overall nesting success could be compromised (Martin, 1987).

COTE respond to predators in two different ways, each of which exposes nests to predation and weather and decreases nest attentiveness. First, adults can aggressively mob predators that threaten eggs or chicks until they eventually leave the colony or move to another

location (Burger & Gochfeld, 1991; Meehan & Nisbet, 2002). Second, adults may form large evasive flying flocks when they recognize that a threat is present. This behavior may last from under one minute to several hours. This may occur even when the species is not a direct threat to eggs or chicks. Leaving the colony for such long periods of time can have severely detrimental effects on reproductive success, exposing eggs to the sun and/or cold temperatures which can slow or halt embryo development (Nisbet, 1975; Meehan & Nisbet, 2002). This exposure may also increase the chances of predation by smaller predators such as BCNH that are normally forced away from the colony by adult mobbing (Nisbet & Welton, 1984). Within the colonies, the number of adults that join or leave the flock varies. Some individuals may remain on their nests while others flock (high nest attentiveness), and other individuals may stay away from their nest long after the others have returned (low nest attentiveness) (Meehan & Nisbet, 2002). For nests attended by adults that tend to flock for longer periods of time, there is an increased chance of predation or egg mortality due to exposure to low temperatures (e.g. cold, rainy nights).

During extended periods of high temperatures, adult COTE may leave the nest and soak their bellies and feet in water to cool their eggs. This soaking may have several functions including cooling the adult, cooling the eggs, increasing the amount of water available for chicks to drink, and increasing nest humidity (Grant, 1981). If the temperature is high enough, even short exposure can damage egg development. Larger chicks (between 9 and 17 d old) tend to hide in clumps of vegetation and only leave cover to move to another clump or to their parents (Nisbet, 1983). Nisbet (1983) reported that, during a day with temperatures upwards of 35°C, all but two chicks older than 10 d died. Much like with

foraging, adults have a cost-benefit relationship between cooling themselves and cooling their eggs and young. Exposing the eggs and young in any situation is detrimental but this is particularly true in higher temperatures.

CONCLUSION

In recent decades, COTE have experienced a great number of stressors throughout their breeding range that have all contributed to the current decline being observed in the Mid-Atlantic region. Habitat destruction through urbanization of shorelines and beaches, worldwide sea level rise, environmental contamination, and anthropogenic disturbance at the breeding colony have all negatively affected COTE breeding colonies. The summer influx of people to summer destinations such as Ocean City puts an extreme stress on breeding COTE individuals and has forced the species to nest on isolated manmade islands that are both highly visible to boaters and susceptible to extreme high tides and sea level rise. Skimmer Island and other similarly sized islands must be continuously replenished with material in order to prevent further deterioration and displacement of breeding individuals. Continued signage to prevent human encroachment and law enforcement presence near these islands will also help to ensure COTE continue to use this site into the future.

Predation has been another major stressor that has negatively affected breeding COTE in the Mid-Atlantic region and throughout the world. An influx of gulls in the Western Hemisphere have been brought on by a sharp increase in the production of fishing and urban waste in the region as well as easier access to breeding colonies brought on by a

combination of sea level rise and habitat displacement by predators. As a result, in recent years, these species fully established themselves in the region (O'Connell & Beck, 2003). The presence of gulls in the mid-Atlantic region is particularly troublesome since their presence has been shown to cause displacement of breeding COTE to suboptimal habitat and predation of both chicks and adults. As a result of these stresses, a precipitous decline in breeding success often occurs (O'Connell & Beck, 2003). Identification of individual predatory gulls is crucial for managers to prevent sharp declines in both COTE nesting success and breeding population numbers at these particularly vulnerable colonies. Removal of these predatory individuals may ultimately cause entire gull colonies to relocate thus preventing future predation and habitat displacement of COTE. Current and future management to control gull predation may aid the species temporarily but without long term control and eradication efforts, COTE will continue to suffer in the region.

Control of other predators such as BCNH, GHOW, and red fox is also paramount to ensuring that COTE numbers stabilize or increase in the future. BCNH present a major threat to breeding colonies due to their specialization in predating on pipped eggs and young chicks of COTE (Hunter & Morris, 1976; Shealer & Kress, 1991). Their presence often leads to nocturnal nest abandonment which negatively affects the hatching success of the colony as a whole (Shealer & Kress, 1991). GHOW presence, likewise, can have an extreme impact on breeding colonies. Both GHOW and the closely related short eared owl prey on all life stages of COTE (Nisbet & Cohen, 1975; Holt, 1994; Arnold et al., 2006). COTE adults may abandon their nests at night in the presence of GHOW thus leading to exposure of both eggs and chicks to predation and weather and subsequently impacting the

success of the colony. Red fox predation poses a particularly difficult issue for managers of COTE colonies because this species caches adult terns and therefore their exact impact on the colony may be difficult to estimate (Nisbet et al., 2017). Entire colonies of COTE and HERG have been abandoned once a red fox is detected (Burger & Gochfeld, 1991). In 2015, the presence of red foxes on Poplar Island caused a number of failed renesting attempts and negatively impacted breeding success estimates for COTE (Prosser, 2015). Rapid identification of predators near COTE breeding colonies is paramount for researchers and managers to prevent further impacts to the species in the future.

A simple measure of the impact predation and other disturbances have on a breeding colony is nest attentiveness. Predation has a negative effect on this measure since predator presence often causes adults to move off the nest thus causing nest attentiveness to decline. As stated previously, GHOW and BCNH presence at the colony both cause nocturnal nest abandonment and expose the nests to predation and weather. Should researchers notice an increase in the number of abandoned nests, cold and untended eggs, or a decrease in total number of eggs, they must take all of this into strong consideration when discussing future management practices. Development of a surveillance system or other monitoring system would be an effective next measure for identifying the presence of predators and, if they are present, the species of predator. Better understanding of the predator's behavior is also important for managing the species and controlling the impact it has on COTE breeding individuals.

Overall, both researchers and managers face major dilemmas with COTE breeding colonies. While certain threats can be more readily managed such as predation and human disturbance, other threats like sea level rise are inevitable and are near impossible to control. Removal of a predator will greatly help breeding success but ensuring colonies are not inundated with sea water is much harder to achieve. The creation of manmade dredged islands such as Poplar and Skimmer Islands has helped the species reestablish itself in Maryland but both of these sites will need continuous management and addition of material to prevent erosion and habitat loss from sea level rise. Furthermore, understanding the exact scope of anthropogenic disturbances on COTE breeding colonies is crucial for both researchers and managers. Educating the public about the breeding colonies and the threats COTE face will be an important next step for managers to ensure that breeding colonies are not disturbed at all during the entire breeding season. Measures such as the implementation of the no wake zone in the Isle of Wight Bay ensure that the anthropogenic impact on these colonies is kept to a minimum. Both researchers and managers will ultimately need to develop management plans for COTE breeding colonies that take both natural and anthropogenic threats into consideration.

2. ASSESSING ISLAND LOSS IN THE CHESAPEAKE BAY AND DELMARVA COASTAL BAYS FROM 1986 TO 2016 USING LANDSAT IMAGE PROCESSING

INTRODUCTION

The Chesapeake Bay and coastal bays of the Delmarva Peninsula are some of the most economically valuable and ecologically important waterbodies in the United States (Chesapeake Bay Foundation, 2018). The Chesapeake Bay is the nation's largest estuary,

extending from the mouth of the Susquehanna River in Maryland (37°0' N, 76°0'W) to the Atlantic Ocean in Virginia (39°32'N, 76° 1'W). Its watershed covers more than 165,000 km^2 and contains more than 150 rivers and streams. Portions of Virginia, Maryland, Delaware, Pennsylvania, and New York lie within the watershed boundaries (United States Department of Agriculture, 2016). The Bay is considered a partially mixed estuary with an average tidal range of 0.6m (Pritchard, 1967; Baird & Ulanowisz, 1989). Commercial fisheries and tourism are the primary economical drivers in the Chesapeake Bay. Fishery landings in 2016 exceeded USD $299 million or approximately 5.6% of the national total (National Oceanic and Atmospheric Administration, 2016). Blue crab (*Callinectes sapidus*) harvesting in the Chesapeake Bay accounts for roughly one-third of the nation's blue crab supply. Recreational boating in the Maryland portion of the Bay contributes USD $2.03 billion annually to the national economy (Chesapeake Bay Foundation, 2018).

The coastal bays of the Delmarva Peninsula extend approximately 200 km from the mouth of the Delaware Bay (38°52'N 75°02'W) to the mouth of the Chesapeake Bay (39°32'N, 76° 1'W) (Orth et al., 2006). These bays are mainly composed of barrier island lagoons and salt marshes. The lagoons have extremely shallow shoals (mean low water level of 1m) that drain into deeper, wider channels with tidal ranges of 0.5 to 1.5m. No major urban centers exist in the coastal bay watershed but a general south to north trend of increasing population density is observed. The primary land use in the watershed is agriculture with a recently documented increase in commercial scale poultry production. Exports from these poultry farms were valued at USD $1.77 billion in 2016 (U.S. Poultry & Egg Association, 2018).

Climate change and its impacts on the region

In recent decades, global climate change has been considered both a major ecological and economical threat to the region. Estuarine systems, like the Chesapeake Bay and Delmarva Peninsula coastal bays, are particularly prone to climate change due to their response to multiple forcing factors including, but not limited to, streamflow quantity and quality, air-water fluxes of CO_2 and heat, and annual fluctuations in sea level (Naijar et al., 2010). Precipitation intensity, or the annual mean precipitation divided by the number of days with measureable rainfall, is expected to rise in the Mid-Atlantic region by one standard deviation by the end of the 21st century. An increase in the annual amount of precipitation and number of dry days has been documented in recent years as well (Meehl et al., 2007; Naijar et al., 2010). During the second half of the 20th century, the Chesapeake Bay experienced an increase in mean sea surface height of 3.5 mm/year (Zervas, 2001). Since then, sea levels have been rising at a rate of 2 mm/year and with it, an increase in tidal range has been observed. This change in tidal range, in turn, has led to increased wave height and energy (Naijar et al., 2010). Sea surface temperature has increased globally since 1970 and this has caused tropical cyclones to strengthen. Peak wind speed from these cyclones is also expected to increase in future years.

Both freshwater and estuarine wetlands have been dramatically impacted by climate change in the Chesapeake Bay region. Freshwater wetlands dependent on precipitation for their water supply are more vulnerable to climate change than those dependent on groundwater (Winter, 2000). Researchers think that as a result of climate change altering

wetland hydrology, these ecosystems have a reduced efficiency of nutrient sequestration. Estuarine wetlands are primarily affected by sea level rise (SLR). Digital elevation models show that roughly 2,500 km^2 of land in the Chesapeake Bay is below 1.5 meters above mean sea level (MAMSL) (Titus and Richman, 2001). More than half of this area (1,700 km^2) is composed entirely of wetland and situated below 0.7 MASML. It is unknown how much of this wetland area will be able to compensate for SLR through vertical soil deposition or inward migration (Kearney et al., 1994). Wetlands that are unable to compensate will likely experience an increase in the presence of invasive species such as *Phragmites australis* (Naijar et al., 2010). Presence of this species has shown negative effects ranging from loss of plant species diversity, changes in marsh hydrology, and an overall reduction in insect, avian, and other animal taxa diversity (Chambers et al., 1999; Naijar et al., 2010).

Island loss and future implications

The increasing threat of SLR in the Chesapeake Bay region is of particular concern regarding island loss; many wildlife species rely on these islands for breeding, nesting, foraging, and stopover during migration. Researchers have recently documented dramatic island loss in the region since the mid-1800s as a result of climate change. Erwin et al. (2011) analyzed habitat loss from islands used by breeding waterbirds throughout the Chesapeake Bay in Maryland and Virginia. The authors found that out of 200 possible nesting islands in the Bay, 17 have completely disappeared since 1977. Sharps Island, a previously inhabited island in Maryland that once hosted waterbird breeding colonies before 1950, was completely submerged due to SLR and erosion in 1962. A subset of 15

previously used nesting islands in the Tangier Sound region of Virginia (37°51'N, 75°49'W) lost approximately 21% of total area between 1994 and 2007 (Erwin et al., 2011). Wray et al. (1995) documented extensive habitat loss of wetland islands in the Maryland portion of the Chesapeake Bay. Barren (38°20'2.18"N, 76°15'30.36"W), James (38°30'53.66"N, 76°20'16.28"W), and Poplar (38°45'45.40"N, 76°23'9.27"W) Islands all experienced area reductions >76% since 1848 (see below for more information regarding Poplar Island). All islands were less than 100 hectares (ha) in 1995 and between 1848 and 1987, they experienced an average loss of 1.9 ha/yr (Wray, 1992). Over this same time span, Bloodsworth (38°10'34.85"N, 76° 3'29.38"W), Smith (37°58'51.72"N, 76° 1'46.21"W), and South Marsh (38° 7'13.72"N, 76° 1'21.77"W) islands all lost, on average, 24.3% of land area at a mean rate of 5.6 ha/yr (Wray et al., 1995). Loss of this critical habitat would be extremely detrimental to breeding populations of the Maryland state endangered common tern (*Sterna hirundo*) and other colonial nesting waterbird species (Erwin et al., 2011). Common terns are reliant on remotely located islands composed of beach or wetland that are far removed from predators for effective breeding (Nisbet et al., 2017). Unfortunately, due to SLR and erosion in the Chesapeake Bay, breeding population and colony numbers for the species dropped by 60% and 20%, respectively, between 1993 and 2003 (Erwin et al., 2011). Due to the recent endangered listing for common terns in Maryland (August, 2016), this island loss could prove devastating for the species in future years as it requires highly specified habitat for breeding (Maryland Natural Heritage Program, 2016).

To help combat further island loss in the Chesapeake Bay, multiple islands have been "restored" by the U.S. Army Corps of Engineers (USACE) in recent years. The most notable of these projects is the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island (hereafter Poplar Island). This island was originally inhabited in the early 1900s and was over 400 ha in size. By the 1990s, the island had diminished to less than 2 ha in size (Erwin et al., 2011; USACE, 2018). In 1996, restoration of the island began through the addition of fine material dredged from the deep navigation channels of the Chesapeake Bay (Maryland Department of Transportation, 2015). The project was touted as a beneficial use project due to the incorporation of clean dredged material for wildlife habitat creation. Upon completion, the reconstruction of the island will cover the original 1847 footprint along with a northward expanse of more than 230 ha and produce around 650 ha of available wildlife habitat 314 ha of tidal wetlands and 335 ha of upland habitat (Maryland Environmental Service, 2017). Since its construction, more than 200 species of birds have been observed on the island (eBird, 2012). Other successful USACE projects within the Chesapeake Bay include Hart-Miller Island, Maryland (39°14'53.20"N, 76°21'57.89"W) and Craney Island, Virginia (36°53'33.0"N, 76°21'34.0"W) (Erwin et al., 2011).

In the Isle of Wight Bay (38°22'N 75°05'W) along the Atlantic Coast of Maryland, the Maryland Department of Natural Resources (MD DNR) has been adding material to Skimmer Island (38°20'11.8"N 75°05'39.7"W) in recent years (MD DNR, 2013). Skimmer Island is a collection of small sand islands used by multiple species of colonial nesting waterbirds including Maryland state endangered common and royal (*Thalasseus maximus*) terns and black skimmers (*Rynshops niger*). The collection of islands did not exist until the

creation of the Ocean City inlet in the 1980s. By 1990, however, enough sand had accreted to form Skimmer Island and since then, it has been a key nesting site for the aforementioned species. The island also provides crucial foraging habitat for migrating shorebirds and is considered a critical spawning habitat for horseshoe crabs (family *Limulidae*) (MD DNR, 2013). Before 2009, SLR caused significant erosion and Skimmer Island was reduced to less than 1 ha. MD DNR, the Ocean City Fishing Center, and the Maryland Coastal Bays Program developed a partnership in 2009 to conserve the island. Every March since, sand dredged from the Ocean City channel has been added to the island (MD DNR, 2013).

Given the known impacts of climate change on the Chesapeake Bay and Delmarva Peninsula region, it is imperative to comprehensively document island loss throughout the region and provide effective management recommendations to ensure this does not worsen in the future. The previously cited studies did not document island loss beyond the early 2000s and did not highlight trends across evenly sampled multi-year intervals. This study accomplishes those objectives by (1) describing island loss from 1986 to 2016 using image processing techniques within a Geographic Information Systems (GIS) software; (2) utilizing a longer, evenly-sampled timespan than any previous study on the subject; (3) using five-year sampling intervals to better illustrate trends and provide future recommendations based on the gathered results.

METHODS

Imagery

After an exhaustive search, historical high definition (HD) imagery was not readily available for download and use within a GIS program. Historical HD imagery (i.e. TerraMetrics® and DigitalGlobe® imagery) was easily accessible within Google Earth Pro but these images could not be downloaded or manipulated outside of the program. The Chesapeake Conservancy collected land use land cover (LULC) and light detection and ranging (LiDAR) data of the entire Chesapeake Bay watershed but no imagery was collected (Chesapeake Conservancy, 2016). The United States Department of Agriculture's (USDA) National Agricultural Imagery Program (NAIP) has collected high definition (~1m resolution) imagery of the Chesapeake Bay watershed mainland since 2005 but no imagery of the Chesapeake Bay or coastal bays was collected. In 2016, the entire Chesapeake Bay watershed was digitized by the Chesapeake Conservancy using NAIP imagery from 2011 to 2014 and orthophotos from 2005 to 2015 (Chesapeake Conservancy, 2016). Unfortunately, this digitization was not completed using historical imagery pre-2005 and therefore this dataset was not used in this study. As a result, Landsat 4-5 Thematic Mapper (TM) scenes from 1986, 1991, 1996, 2006, and 2011 and Landsat 8 Operational Land Imager (OLS) scenes from 2016 were obtained from the United States Geological Survey's (USGS) EarthExplorer imagery database (https://earthexplorer.usgs.gov/) as Geostationary Earth Orbit Tagged Image File Format (GeoTIFF) data products. 2001 imagery was not included in this analysis due to time constraints. Tables 2A and 2B detail the spectral components of these satellites. Selected scenes were gathered between early spring and mid-autumn (May to October) in daytime conditions with less than 10% scene

cloud cover. Scenes were collected along World Reference System (WRS) paths 14 and 15 rows 33 and 34 (hereafter 14/33, 14/34, and 15/33, respectively). WRS path 15 row 34 was not used for any year since this imagery was situated too far inland and did not include any additional islands that were not detected in other scenes.

Image preparation

Once scenes were obtained, bands 1 through 7 (Landsat 4-5 TM scenes) or bands 2 through 7 (Landsat 8 OLS scenes) were imported into ArcMap 10.5 (ESRI, Redlands, CA) (see Figure 2A for a schematic highlighting all major steps in this analysis). The coordinate system used for all scenes was WGS 1984 UTM Zone 18N. A composite scene of all bands was created using the Composite Bands tool within ArcMap and this newly created scene was displayed in true color (R, G, B = 3, 2, 1). To distinguish land cover types, images were stretched to between two and five standard deviations (ESRI, 2018a). Band stretching magnifies the spectral properties of each band (i.e. adjusting contrast of the image) thus ensuring classifications are as accurate as possible. Standard deviation numbers <2 produced images that were too bright and faded whereas scenes stretched with numbers >5 were too dark and dim to distinguish land cover types.

After stretching, scenes were then segmented using the SegmentMeanShift tool within the Python scripting window in ArcMap (see Appendix). Image segmentation is an image processing technique where spectrally similar pixels in close proximity are grouped together into so-called objects or segments. This processing technique and subsequent image classification are similar to traditional pixel-based image classification techniques

in that objects may be considered super pixels. Each segment, or super pixel, contains a particular set of attributes that allow the classifier tools within ArcMap to generate a classified image. Segmentation within ArcMap utilizes a mean shift approach in which a moving window calculates the average pixel value to determine which pixels are placed into which segment. As the window moves along the scene, it recalculates the mean pixel values to ensure proper segment selection for each pixel.

Segmentation is further determined by spectral and spatial detail, minimum segment size, and band indexes. Spectral detail determines the importance given to the spectral differences between individual pixels. Values range from 1.0 to 20.0 where low values give low importance and high values give great importance to spectral properties. High values are best used for images containing features that should be classified separately but have similar spectral qualities (e.g. beach and urban land covers). For this study, several of the classified land cover types (defined below) have high spectral similarities and classifying them accurately is imperative in order to correctly describe trends in land cover area. Spatial detail sets the importance value given to the proximity of pixels to one another when segmenting the image. Much like spectral detail, spatial detail values range from 1.0 to 20.0 where low values give low importance to the spatial relationship between pixels and high values give great importance to this relationship. High values are appropriate for scenes containing small, clustered features of interest. Many of the islands of interest in this study are small in size (<4,500 m^2) and therefore spatial detail is as important as spectral detail. Minimum segment size determines the size, in pixels, of the smallest possible segment. Segments smaller than this value are merged into the best fitting

neighboring segment. This value ensures that minute objects, which may be easily misclassified, are not created. Band indexes allow for the selection of three bands for use in the segmentation tool. The chosen bands should highlight the greatest differentiation between features of interest. For this study, scenes displayed in true color highlighted the greatest difference between land cover types. After extensive testing for segmentation accuracy and detail through multiple value alternations for each parameter, the final values for the aforementioned properties were selected as 18.0 for spectral detail, 18.0 for spatial detail, 1 pixel as the minimum segment size, and bands 3, 2, 1 (Landsat 4-5 TM)/ 4, 3, 2 (Landsat 8 OLS) for band indexing, respectively.

Image classification

Training samples were drawn over the segmented scene using the Training Sample Manager within the Image Classification toolbar in ArcMap. Between 40 and 120 polygons per land cover were drawn throughout the entirety of the scene. Each polygon was drawn over objects containing a single land cover to reduce land cover misclassifications. Once all training sample polygons were drawn, a training file containing these polygons was saved. The land covers of interest included the following:

Water: any body of water ranging from rivers, to lakes, to the Chesapeake Bay and the Atlantic Ocean.

Forest: forested or vegetated land. Hard and softwood forests and vegetated coastal dunes were included in this category. Any other vegetated open space was placed into a separate category (see below).

Agriculture/Open Field: a general category including all agricultural fields, outdoor recreational spaces (e.g. soccer fields), quarries, yards, and all other undeveloped vegetated or non-vegetated open spaces.

Wetland: any area at the land-water interface where water covers the soil or is present at or near the surface for the majority of the year or some portion of the year (Tiner, 2017). Permanent and ephemeral fresh and saltwater wetlands were included.

Beach: sand deposition at the land-water interface.

Urban: any urbanized land area. Light, medium, and high intensity development were included. Parking lots, roads, and other developed open spaces were also included.

To classify the segmented raster based on the newly digitized training polygons, a random tree classification approach was utilized (ESRI, 2018b). This supervised machine learning technique is based on the creation of a myriad of decision trees where each is developed based on a subset of training samples. The training samples used in this analysis were the digitized land cover training polygons. The computer randomly selects a subset of training variables for each tree and then uses the most frequently selected variable output for the overall classification. Trees are often first overly fit to the training samples and therefore the creation of a "forest", with some over fit and some under fit trees, prevents model overfitting from occurring. For segmented rasters, the computer calculates the index image and associated segment attributes from the RGB segmented raster (i.e. segmented Landsat

scene). The determined segment attributes generate the classifier definition file for later raster classification.

The accuracy of the classifier definition file is determined through the selection of multiple variables. The maximum number of random trees is the largest number of trees within the forest. Higher values increase accuracy but this eventually levels off and no further improvement is observed. A value of 50 was selected for this variable as numbers greater than this value did not improve overall accuracy whereas lower values produced lower quality classifications. Maximum tree depth determines the number of rules each tree is allowed to make before making a decision. Trees will not grow larger than this value. This variable was given a value of 30. Increasing this value did not produce any noticeable differences in classification accuracy whereas decreasing this value caused accuracy to diminish. The maximum number of samples is the largest number of samples the computer may use when defining each class. To ensure that land covers were detected throughout the entirety of the scene, this variable was set to 2500 (J. Resop pers. comm). Lower values caused small portions of scenes to be misclassified or entirely unclassified whereas high values, like all other parameters, did not alter accuracy. These values were input into the Train Random Trees Classifier tool. The original unsegmented Landsat scene was added as an additional input raster to increase the classifying accuracy of the random trees. After all options were verified on the segment attributes menu, the tool was executed and a classifier file was created.

Next, the segmented raster was classified using the random tree classifier file. The original unsegmented Landsat scene was again added to increase overall classification accuracy. Once classified, the raster was run through a majority filter for smoothing and to remove any individually misclassified pixels. The filter used eight neighboring cells and a majority replacement method. This meant that the majority of the neighboring cells had to be classified as a single land cover type for the center cell to be reclassified as such. The filtered raster was then reclassified to create a mask of land and water. All land cover classes were reclassified with a value of 1 and water was reclassified with a value of 0. Once reclassified, the raster was converted to unsimplified polygon form. Land polygons outside the water polygons (i.e. the mainland) were manually deleted. A Python script which selected all land polygons enclosed within water polygons (i.e. islands) was run to create a layer of all islands within the scene (see Appendix). After running this script, polygons that were misclassified as islands (i.e. boats, small bridges, and clouds) were deleted. Of the remaining islands, only "habitat islands" were kept. These islands contained measureable beach and/or wetland habitat while also occasionally containing other land covers types as well. Islands without measureable beach or wetland, entirely forested islands, or fully developed islands were manually deleted ($n < 100$).

Upon completion, the classified and filtered raster was clipped to the new island layer and was then converted to polygon form. This newly created polygon land cover layer was manually edited at a scale of 1:600 to correctly classify land covers within individual polygons and to redraw misshapen polygons over the correct land cover. To ensure the accuracy of the manually reclassified polygons, HD historical imagery from the exact year

of the Landsat scene was displayed within Google Earth Pro. In cases where imagery did not exist for the exact year, historical imagery was displayed from the next closest year. After manually editing the shape of the polygons, the land cover areas were calculated and polygons were reconverted to raster form with cell sizes of 30m to match the original Landsat cell size.

Accuracy assessment

Accuracy assessment points were created over the edited island polygon layer within ArcMap 10.5 using the Create Accuracy Assessment Points tool. For all scenes except 14/33, 1,200 equalized stratified random points were created (200 points/land cover). For 14/33, 600 stratified random points were created (100 points/land cover). This adjustment was made because so few polygons existed within this scene ($n < 100$) and those polygons were only classified as wetland, forest, beach, or some combination. The equalized stratified random technique places an equal number of points within each land cover type. If the number of polygons per land cover class is unequal or too low, the computer will not create the points as was the case for 14/33. The accuracy assessment point layer was converted to Keyhole Markup Language (KML) format and imported into Google Earth Pro for groundtruthing purposes. Historical imagery gathered from the same year, or next closest year, as the Landsat scene was displayed. In cases where imagery from the exact year was unavailable, a color Google Earth image of the area of interest from the next closest year or the original Landsat scene was displayed in true color and was extensively reviewed to ensure proper land cover classification. For each point ($n = 18,000$), the

groundtruthed land cover was documented within Microsoft Excel 2010 (Microsoft, Redmond, WA) and compared to the manually classified land cover from ArcMap.

Unweighted Cohen's Kappa coefficient, a measure of inter-rater (also known as inter-observer) agreement, was calculated within R 3.4.3 using the "lpsolve" and "irr" packages (R Core Team, Vienna, Austria). The raters/observers in this study were the classified image from ArcMap and the groundtruthed imagery from Google Earth. This coefficient was used instead of calculating percent agreement because of its incorporation of chance agreement between raters (McHugh, 2012). In this study, the classified polygons within ArcMap acted as one rater and the groundtruthed accuracy assessment points within Google Earth Pro acted as the other rater. Values for this coefficient range from 0 to 1 where 0 is complete disagreement and 1 is complete agreement between raters. The coefficient is calculated using the following formula:

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \quad (1)$$

Where Pr(a) is the actual observed agreement between raters and Pr(e) is chance agreement (McHugh, 2012).

The accuracy of the Python script to select habitat islands was also determined. A point layer of all habitat island centroids in the Chesapeake Bay and Delmarva coastal bays was created manually within Google Earth by placing pins on island centroids. Highly ephemeral islands or islands not observed in the majority of Landsat years (≥5 years) were not included in this layer. The percentage of correctly selected islands out of the total habitat islands observed was calculated within R 3.4.3.

RESULTS

Island accuracy

A total of 536 habitat islands (i.e. islands with measureable beach or wetland habitat) were identified using Google Earth imagery of which 29.1% (156) were located in the Chesapeake Bay and 70.9% (380) were located in the Delmarva coastal bays (Figure 2B). Of the Delmarva islands, 26.8% (102) were located in Maryland and 73.2% (278) were located in Virginia.

The accuracy of the island selection Python script varied greatly across years and scenes (Tables 2C to 2F). The least accurate scene was 14/33, with an average of 30.7% accuracy. Scene 15/33 was the most accurate with a mean accuracy of 79.9%. Because 14/34 covered both the Chesapeake Bay and Delmarva coastal bays, island accuracy for this scene was split between the two waterbodies. Chesapeake Bay islands were more readily detected than Delmarva islands ($\overline{x}$ = 44.2% and 28.1%, respectively) across all years.

Habitat area calculations

Because the Python script did not consistently select the same islands across years, habitat area was calculated from a subset of 140 islands that were selected by the computer in five or more survey years (Figure 2B). Note that all subsequent area calculations are based on this smaller subset of islands only. Across all years, wetland comprised the largest area ($\overline{x}$ = 11,045.59 ha) while urban comprised the least ($\overline{x}$ = 217.24 ha). Beach comprised the second most area with a mean of 1,290.52 ha, agriculture/open field comprised the third

most area ($\overline{x}$ = 833.67 ha), and forest comprised the fourth most ($\overline{x}$ = 377.81 ha) (Figure 2C).

All land cover types experienced a net area loss from 1986 to 2016. A total of 1,213.69 ha were lost over this timespan. Agriculture/Open Field declined by 81.24% (1,1162.82 ha), the most among all land cover types. Forest declined the least (-4.43%/16.4 ha) over the 30-year timespan. From 1986 to 2006, wetland experienced a net increase in area of 17% before losing 16.11% between 2006 and 2011. In total, wetland area increased by 0.19% (19.84 ha) (see Discussion). Urban area experienced a decrease of 71.06% (214.59 ha) from 1986 to 2011 but then had an increase of 125.79% (136.53 ha) between 2011 and 2016.

In the 140 islands used for area calculations, beach habitat fluctuated in a very distinct and unexpected pattern across the three decades (Figure 2C). A decline was noted between 1986 and 1991 before an increase in area of nearly 20% between 1991 and 1996. Another decline was documented between 1996 and 2006 of 13.74% before yet another increase in area of over 11% between 2006 and 2011. After 2011, area declined by 6.61%. A net increase of 1.78% in beach area was documented between 1986 and 2016. In total, 23.74 ha of beach habitat were lost over this time period.

Cohen's Kappa calculations

Cohen's Kappa values varied widely from year to year and scene to scene (Table 2G). The average Kappa value across all scenes and years was 0.539 which shows a moderate

agreement between the groundtruthed and classified data (McHugh, 2012). Kappa values were particularly low for 14/33 with a mean of 0.255. Both 14/34 and 15/33 showed high agreement with mean Kappa values of 0.683 and 0.681 respectively. Without including 14/33 in calculations, the mean Kappa value for both 14/34 and 15/33 across all years was 0.682 which shows considerable agreement between the groundtruthed and classified data.

DISCUSSION

Island land cover observations

As illustrated by this study, island area has declined in the Chesapeake Bay and Delmarva coastal bays since the late 1980s. Most land covers (wetland and beach being the exceptions) experienced a net loss in area over this period with some experiencing greater losses than others. Agriculture/Open field, the catchall category encompassing all non-urbanized open spaces and fields, showed a steady decline across the entire time span. Forest fluctuated from year to year while only experiencing a net area loss of 4.43% over 30 years. Urban experienced a slight increase from 1986 to 1991 but for the proceeding two decades, showed a net decline in area followed by another increase between 2011 and 2016. Contrary to initial expectations, a net decrease of 24.16% in urban area was detected over the study period.

Wetland area fluctuated across this 30-year period. A net increase of approximately 17% between 1986 and 2006 was nearly completely reversed in the following five years (-16.11%). Tropical Storm Hanna and Hurricane Irene may be an explanation behind the observed trend. Hanna remained offshore on 06 September 2008 but did affect the

Delmarva Peninsula. Sustained winds of 37 knots (kn) (68 kph) and gusts upwards of 55 kn (102 kph) were recorded. Tides were raised up to 1 m above astronomical tide level and minor beach erosion was observed as a result (NOAA, 2008). Irene, however, had much more devastating impacts on the region. The storm passed to the east of Ocean City, Maryland (38°20'N, 75°5'W) on 27 August 2011. Sustained winds reached 70 kn (129 kph). Rainfall totals were greater than 30cm in the Chesapeake Bay and significant beach erosion was observed. In Maryland, property damage from the storm exceeded USD $10 million (NOAA, 2011). With these storms, tidal inundation, perimeter erosion, and degradation of wetlands may have occurred, thus leading to the observed decline.

An intriguing trend emerged in beach habitat over the three decades. Two increases were observed between 1991 and 1996 and 2006 and 2011. These can be attributed in part to (1) large accretions of sand on Delmarva coastal islands in Virginia and (2) the construction of Poplar Island. After an extensive review of manually edited polygons and historical imagery, sand accretion was observed throughout the study area, in particular on coastal bay islands in Virginia. Deposition was pronounced on these islands due to their exposed location along the Atlantic coast and their conspicuous sandbars. Regarding Poplar Island, in 2006, the majority of the island was classified as wetland with beach comprising less than half of the island's total area. In 2011, the island was more evenly split between wetland and beach. A large deposition of sand and dredged material on the island occurred between these years thus contributing to the second observed increase in beach area.

The observed trend in beach habitat is a particularly interesting finding as one of the main principles behind Poplar Island's reconstruction was the development of new critical wildlife habitat (USACE, 2018). Since 2001, more than 200 avian species have been observed on the island according to eBird records (eBird, 2012). Of these species, roughly 24% are shorebirds and waterbirds (order *Charadriiformes*) that actively use beach for foraging and stopover habitat. While the increase in beach habitat in 2011 was an exciting discovery, the construction of this single island was nearly unable to offset the net loss of beach habitat since 1986 and, in fact, a small decline in beach area was still observed between 2011 and 2016. In fact, removing this island from area calculations still produces the same observed trends in available beach habitat (Figure 2D). Other small habitat restoration projects in the Chesapeake Bay (e.g. Hart-Miller Island) and Delmarva coastal bays in Maryland (e.g. Skimmer Island) hold promise by creating valuable beach habitat. Unfortunately, due to high project costs and diminishing budgets, the future of these projects is uncertain.

Improvements to Cohen's Kappa calculations

The Cohen's Kappa values for all 14/34 and 15/33 scenes were well within the range of "substantial agreement" (Kappa between .60 and .79) between the classified and groundtruthed land covers and therefore the presented results can be considered highly accurate (McHugh, 2012). For 14/33 scenes, Kappa values were considerably lower across all years. While the values were considered "poor", this was likely due to misclassification. To calculate Kappa values, a matrix of N x N rows (where N is the number of land covers) is created where the proportion of numbers along the diagonal (agreement between raters)

out of the total is calculated. When accuracy points fall within a land cover that is not directly classified (e.g. groundtruthed water versus classified wetland), the Kappa value begins to diminish. This was the case with 14/33 as some accuracy assessment points fell outside the digitized island shoreline and were groundtruthed as water. One potential solution to this issue would be producing a layer of groundtruthed accuracy assessment points within Google Earth that fall directly on land (e.g. wetland as is the case of 14/33) and importing this layer into ArcGIS to determine the classified land cover type. This is essentially the opposite order of how accuracy was assessed for every scene in this project. Assessing accuracy in this order for 14/33 only would ensure that all accuracy assessment points lie within a groundtruthed land mass instead of individually classified, and potentially inaccurate, Landsat pixels (see "Study limitations"). The majority of points in 14/33, however, were correctly matched and therefore the observed accuracy was likely much greater than initially calculated. The remaining points were not correctly matched to the corresponding land cover due to time constraints.

While the Kappa values are quite high, there was some room for improvement. Possible ways to improve accuracy included (1) increasing the number of accuracy points and (2) including water as an island land cover. Increasing the number of accuracy points might have been a simple solution because with more points, there is greater likelihood of obtaining a higher proportion of correctly matched points. The vice versa is also potentially true in which a greater number of accuracy assessment points would fall outside the correctly classified land cover polygons and therefore decrease overall accuracy. This was especially true for scenes containing many small islands with pixels which contained

multiple land cover types (e.g. 14/33) (see "Study limitations"). Water was used to classify entire scenes for the sole purpose of the computer distinguishing islands from the mainland. This land cover was not, however, included in island area calculations and water polygons located within an island's perimeter were deleted. For less conspicuous islands composed of a single land cover, including water polygons where necessary may have helped bolster Kappa calculations. As mentioned previously, occasional accuracy assessment points fell outside the perimeter of classified islands in 14/33. Had water been included as a land cover for Kappa calculations and water polygons surrounding and within island perimeters been included, the Kappa values may have greatly increased for 14/33.

Study limitations

The inability to use high definition historical imagery of the Chesapeake Bay and Delmarva coastal bays was the greatest limitation for this study. Single Landsat pixels have an area of 900 m^2 and some minute islands (especially in 14/33 and 14/34) could not be digitized or detected by the computer before and after the segmentation process. Sub-pixel land cover also proved difficult for classification. Within a single pixel, it was common to find multiple land covers. Using the centroid of the accuracy assessment points solved this issue for calculating Cohen's Kappa. However, having multiple land covers within a pixel proved difficult when classifying polygons. While it has been common practice to classify a polygon based on the land cover comprising the majority of said polygon, this may have inflated area calculations incorrectly. It was impossible to classify individual mixed pixels perfectly and, therefore, the proportion of land covers within certain polygons may have been misinterpreted. Classifying and digitizing islands within the study area was a

particularly difficult and time-consuming process due the aforementioned sub-pixel land covers and highly complex island shorelines. Processing a single scene took upwards of 12 hours and some imagery had to be randomly selected for elimination; 2001 imagery was not included in this study. If readily available, future studies could use high definition imagery to avoid these issues and increase overall accuracy of both area calculations and land cover classifications.

Image segmentation inherently creates some risk of losing valuable information. As stated previously, the segmentation process gathered spectrally and spatially similar pixels together into objects. This reduced overall resolution and certain islands were either blended into shoreline land covers or water pixels. Island accuracy was low for 14/33 and 14/34 for this exact reason. In the Virginia Delmarva bays, large wetland islands adjacent to the shoreline were often misclassified as part of the mainland due to segmentation. Other islands with spectral signatures close to the surrounding water were subsequently misclassified as water pixels post-segmentation.

The discrepancy of island accuracy across scenes was mainly attributed to the location of the scenes, the number of islands within each scene, and the predominant land cover of the islands. For 14/33, most undetected habitat islands were entirely composed of wetlands. These islands had very similar spectral properties to the surrounding water and were undetected by the computer as a result. As previously mentioned, the same trend was observed with Delmarva islands in 14/34. Chesapeake Bay islands were, on average, much larger than Delmarva islands and were composed of multiple land covers with spectrally

diverse properties. In 15/33, accuracy was high across all years due to the low number of habitat islands (n = 39) within the scene as well as the size and land cover composition of the islands.

Further reduction of island misclassification might have been possible through altering some of the initial segmentation parameters. Spatial resolution determined the importance of a pixel's spatial relationship to one another when defining objects. Upon initial inspection, it appeared choosing a spatial resolution value (ranging between 0.0 and 20.0) greater than 18.0 did not improve the accuracy of object creation. However, altering this value might affect accuracy if all other segmentation parameters were held constant. This process would essentially act as a sensitivity test for the spatial resolution. Adjusting spectral resolution may have a similar effect on increasing accuracy. This parameter determines the overall importance given to spectral properties when creating objects. Much like spatial resolution, increasing this value did not yield any differing results. Reducing spectral resolution while keeping spatial resolution constant may prevent wetland islands from blending into the shoreline or neighboring water pixels. The opposite may occur, however, as decreasing the importance of spectral properties may lead to the creation of larger objects thus magnifying this island blending. Further research should be conducted on this before finalizing these segmentation parameters for future studies.

Another segmentation parameter that may be adjusted to increase accuracy is the band index. This index uses three separate bands to highlight differences between land covers. While a true color index was used for this study, other band indices may increase overall

accuracy. False color composites (R, G, B = Landsat TM bands 4, 3, 2) are widely used for vegetation studies. False color composite scenes show vegetation in varied shades of red, urban areas in blue, water in black, and agricultural fields in gray. Beach is often displayed in a similar shade of blue as urban areas which would cause consistent misclassification of these land covers by the computer. Wetland is displayed in a separate shade of gray but, under certain conditions, this land cover may mimic agricultural fields and be subsequently misclassified. Therefore, a false color index would not be useful for the current study. A "natural-like" band index (R, G, B = Landsat TM bands 7, 4, 2) highlights urban and agricultural areas in bright pink, beach in bright purple, healthy vegetation in shades of green, water in dark blue, and emergent wetlands in brown. While this index works well for distinguishing beach and urban from surrounding land covers, it is not effective for distinguishing tidal wetlands from water as both are displayed in shades of blue. Using this band index may exacerbate the aforementioned wetland island segmentation issues and is therefore not recommended for similar studies. Further experimentation of band indexes and segmentation accuracy is warranted for future studies similar to this study.

As stated previously, imagery on Google Earth was not collected from every study year. Imagery dates varied across the study site but consistent imagery was collected in 1989, 1994, 1998, 2006, 2011, 2013, and 2016. User interpolation of ground cover was necessary for early study years (1986 and 1991) because groundtruthing imagery did not align perfectly with the Landsat imagery. Imagery collected before 1994 was often in grayscale which caused some confusion during the groundtruthing process. Some pre-1996 land cover classifications may be slightly incorrect as a result of the aforementioned

methodology. Therefore, usage of older Landsat imagery should be adjusted for by using historical orthophotographs or other available high-definition imagery for image classifications.

CONCLUSION

The Chesapeake Bay and coastal bays of the Delmarva Peninsula are two of the most important ecosystems in North America. Their economic impact on the region and the nation as a whole is unrivaled. Due to climate change, estuarine ecosystems like the Chesapeake Bay are greatly impacted. Sea level rise has inundated wetlands and disrupted their normal functions, erosion has disintegrated entire islands, and tropical cyclones have worsened in intensity and strength in recent decades. A great number of species use islands in the Chesapeake Bay and Delmarva coastal bays for breeding, foraging, and migration stopover habitat. Without these islands, many species would become endangered or even locally extinct. It is for these reasons that actions must be taken to prevent island loss from worsening.

This study has documented island habitat change in the Chesapeake Bay and Delmarva coastal bays over a 30-year period from 1986 to 2016. Previous studies have documented island loss in the region (Erwin et al., 2011; Wray, 1992; Wray et al., 1995) but none have observed island loss beyond the mid-2000s or over as long a time span as this study. Since 1986, overall island area has decreased by over 1000 ha. Beach and wetland habitat, both of particular concern regarding nesting waterbird species, have declined by over 300 ha. Poplar Island, a project funded by the USACE, contributed hundreds of hectares of beach

habitat in 2011, an observation never before documented. Unfortunately, this increasing trend in available beach habitat did not continue beyond 2011 despite the creation of several small sand stockpiles for use during habitat construction in 2016 and another decline in habitat was observed in 2016.

Managing what habitat is currently available is the most important measure agencies can take today. Erosion of habitat islands may be avoided through the construction of berms or low cost riprap barriers that deflect wave energy away from the island perimeter. Supplementing islands with dredged material, although expensive and sometimes controversial, may serve as an immediate method to mitigating erosion (i.e. Poplar and Skimmer Islands) and could be used to aid habitat restoration efforts. The Maryland Department of Natural Resources has helped fund the creation of multiple small sand islands in the Delmarva coastal bays to help breeding waterbird populations in the state. USACE has constructed Hart-Miller Island in Maryland and Craney Island in Virginia to provide more nesting habitat in the Chesapeake Bay. While the construction of these islands is greatly beneficial to many species, unfortunately, declines in breeding populations and number of breeding colonies have continually been documented for multiple species in recent years.

Mitigating island loss is a costly and long term goal for the agencies involved. Upfront costs may seem extreme but the benefits of creating vital nesting habitat for locally endangered species often outweigh these initial costs. Poplar Island is just one such example. Numerous plant and wildlife species live on the island and provide the

Chesapeake Bay with crucial ecosystem services. State endangered waterbird species breed on the island every year. Without the creation of this island and similar projects throughout the Chesapeake Bay and Delmarva coastal bays, numerous species could become locally extinct or endangered. Even small, more cost effective management efforts would greatly aid this cause. While it is unlikely that the effects of climate change can be reversed, it is possible to protect ecosystems for future generations through effective management strategies and practices.

3. OBSERVATIONS OF DECLINE IN COMMON TERN (*Sterna hirundo*) COLONY AND POPULATION NUMBERS IN MARYLAND FROM 1986 TO 2017

INTRODUCTION

The Chesapeake Bay first began as the Susquehanna River; as icebergs melted at the end of the last ice age, sea levels rose and flooded the shallow coastal plains of Maryland and Virginia to form the Bay. The islands of the Chesapeake Bay first formed during the creation of the Bay itself over the course of the last Ice Age (2.6 mya to 11.7 kya) (Cronin, 2005). Islands, the majority of which lie along the eastern shore of Maryland and Virginia, subsequently developed from this high water carving out the mainland (Cronin, 2005). These islands, so-called nesting colony sites, provide critical nesting habitat for numerous waterbird species in the region including the Maryland state endangered common tern (*Sterna hirundo*) (hereafter COTE) (Erwin et al., 2003; Erwin et al., 2011; Maryland Natural Heritage Program, 2016; Nisbet et al., 2017).

Island loss in the Chesapeake Bay and Delmarva coastal bays became a public concern as early as 1914 (Cronin, 2005). The Maryland Geological Survey (MDGS) observed that in 1848, Sharps Island had an area of 177 hectares (ha) but by 1910, the island's area was only 21 ha, accounting for a loss of nearly 3 ha/year. The MDGS also observed changes at Tilghman Island. In 1847, the island was over 815 ha in size but by 1900, this area had decreased to 682 ha, a loss of nearly 2.5 ha/year (Cronin, 2005). Numerous more recent studies (Kearney & Stevenson, 1991; Leatherman et al., 1995; Erwin et al., 2003; Cronin, 2005; Erwin et al., 2011) have described island loss in the Chesapeake Bay and Delmarva coastal bays of Maryland in recent decades. Cronin (2005) observed that habitat loss through erosion has entirely or partially destroyed >500 islands totaling >32,000 ha in area. Leatherman et al. (1995) observed that islands which experienced high habitat loss through erosion will continue to have increased rates of erosion in the future, particularly smaller islands. This disproved an original assumption that a larger perimeter-to-area ratio (seen in large islands) would equal greater erosion rates.

Climate change is greatly impacting the Chesapeake Bay and Delmarva coastal bays through sea level rise and more powerful, frequent storms (Naijar et al., 2010). Sea levels have risen worldwide due to climate change but the impact of this is especially felt in the Chesapeake Bay region where sea levels have risen 3.0 mm/year since 1650 AD (Kearney & Stevenson, 1991). Upwards of 1,500 km^2 (65.8%) of land in the Chesapeake Bay is below 1.5 m in elevation, land which is directly threatened by continued sea level rise (SLR) (Titus & Richman, 2001). While much of this land area is wetland, it is still unknown

how these ecosystems will adapt to this environmental change (Kearney et al. 1994; Titus & Richman, 2001).

In June 1972, Tropical Storm Agnes produced nearly 46 cm of rain (Leatherman et al., 1995). This vast amount of freshwater temporarily flushed out all salt water from the Chesapeake Bay causing two million bushels of oysters to die throughout the Bay (Leatherman et al., 1995). On 18 September 2003, Hurricane Isabel made landfall in North Carolina, while storm bands struck the Chesapeake Bay and caused damages estimated at USD $275 million in Maryland and >USD $1 billion in Virginia. Watts, Tangier, and Smith Islands were completely submerged at the height of Isabel. In the Potomac River, near Washington, D.C., Cobb Island was severely damaged due to a 3.4 m storm surge (Cronin, 2005). As water temperatures continue to increase as a result of climate change (Naijar et al., 2010), scientists predict storms of this magnitude to become a more frequent occurrence in the Chesapeake Bay region.

Generally, island habitat may be destroyed in two specific ways: erosion, the degradation of shoreline through wave energy, and submersion, complete inundation of habitat due to high water levels (Leatherman et al., 1995). The prevailing wind direction in the Chesapeake Bay is WNW therefore most waves are directed towards the Eastern Shore. This wind direction and the accompanying fetch, or the distance across water that wind travels, contribute to very high erosion rates on Bay islands (Leatherman et al., 1995). These islands protect the mainland from the brunt of raw wave energy at the cost of high erosion to the islands themselves. At least 13 islands in the Chesapeake Bay have been

completely lost due to SLR (Leatherman et al., 1995). An increase in frequency of flooding events along with a subsequent increase in erosion rates is the primary driver behind this habitat loss (Leatherman et al., 1995). Much of the remaining Chesapeake Bay island area has an elevation between sea level and <2 m thus exposing this habitat in particular to the effects of SLR. Studies have also shown that islands with less total area have fared much worse than larger islands due to SLR (Leatherman et al., 1995; Cronin, 2005).

Waterbird populations and island loss in Maryland

Researchers have monitored waterbird populations throughout Maryland with regularity since the mid-1980s (Erwin et al., 2003; Brinker et al., 2007; Erwin et al., 2011). Currently, 14 waterbird species regularly breed in the Chesapeake and Delmarva coastal bays of Maryland (Brinker et al., 2007). All of these species have experienced significant declines in breeding numbers since the 1800s as a result of human-related activities throughout the eastern United States. The greatest impacts on these species resulted from the millinery trade, egg collecting, habitat destruction, increased shoreline development, and pollution (Brinker et al., 2007). In general, waterbirds may be particularly affected by habitat destruction due to their limited preference in breeding habitats (Erwin et al., 2003; Nisbet et al., 2017).

A recent review of digital orthophotographs of the Chesapeake Bay (Erwin et al., 2011) revealed 200 potential nesting colony sites for waterbirds composed entirely of beach, wetland, or some mixture of the two. In Tangier Sound, located in the Maryland portion of the Chesapeake Bay, 17 of these nesting colony sites were used by breeding waterbirds at

least once between 1977 and 2007. Of these sites, 15 experienced habitat loss totaling roughly 20% of the total habitat area over only 13 years (Erwin et al., 2011). Breeding numbers mirrored this habitat decline; between 1993 and 2003, the number of breeding pairs declined by 60% (Erwin et al., 2011). Contrary to this decline, however, the number of nesting colony sites increased between 1977 and 2003 from 23 to 45 (Brinker et al., 2007). It was posited that increased predation led to an increase in nesting colony site numbers through the division of larger former colonies into smaller colonies.

Erosion of previously used nesting colony sites ultimately reduces the number of future available options for breeding individuals (Erwin et al., 2003). Sand accretion may occur elsewhere and provide new nesting habitat but breeding individuals may not locate it until the following season. The reduction of available breeding habitat has caused major shifts in COTE colony site usage over time. Between 1977 and 1993, a shift from the Delmarva coastal bays to the Chesapeake Bay was observed. In 1977, 3,470 COTE breeding pairs were surveyed in the Delmarva coastal bays as compared to 86 in the Chesapeake Bay (Erwin et al., 2003). In 1993, a major shift was observed as 1,313 breeding pairs were documented in Delmarva as compared to 1,605 in the Chesapeake Bay (Erwin et al., 2003). The proliferation of mammalian predators in the region may have also impacted this shift in colony site usage but this was not well documented by the researchers (Erwin et al., 2003).

Island habitat, crucial for nesting waterbirds, is particularly difficult to manage due to aforementioned erosion and habitat destruction along with several other factors. Larger

islands, some with expansive forest and wetland systems, provide ample habitat for tree-nesting waterbird species but are rarely used by ground-nesting waterbird species like COTE due to a lack of open sandy habitat as well as the presence of mammalian predators (Erwin et al., 2003; Erwin et al., 2011). As a result, these large islands, when used by ground-nesting waterbirds, may ultimately develop into "sink" colonies, where total recruitment success falls below the total number of breeding individuals (Erwin et al., 2011). As mentioned previously, increase in mammalian predation may lead to the dissolving of large breeding colonies into smaller, less successful colonies. These smaller colonies are typically located on small to medium sized islands which are more directly affected by SLR and erosion. With erosion and destruction of these islands, one can expect an observed decline in breeding pair numbers as well (Erwin et al., 2003).

Through a combination of satellite imagery, geographic information system (GIS) analyses, and COTE breeding population data since 1986, this study aimed to improve the understanding of trends in COTE breeding numbers in Maryland. It is posited that as available breeding habitat area declines, so will the breeding population of COTE in the state. Based on that idea, the following research objectives were developed: 1) document nesting colony site area loss in the Chesapeake Bay and Delmarva coastal bays of Maryland from 1986 to 2016, 2) observe trends in numbers of breeding COTE over this timespan, and 3) provide recommendations for future management of the species throughout Maryland.

METHODS

Habitat area measurements:

Landsat 4-5 Thematic Mapper (TM) scenes from 1986, 1991, 1996, 2006, and 2011 and Landsat 8 Operational Land Imager (OLS) scenes from 2016 were obtained from the United States Geological Survey's (USGS) EarthExplorer imagery database (https://earthexplorer.usgs.gov/) as Geostationary Earth Orbit Tagged Image File Format (GeoTIFF) data products. 2001 imagery, although available, was not included in this analysis due to time constraints. For each scene, a composite of all seven spectral bands was created. This band composite was then stretched to between two and five standard deviations in order to magnify the spectral properties of each band thus ensuring more accurate image classifications. A shapefile of island polygons was created from the imagery for all islands containing measurable beach and/or wetland habitat within the Chesapeake Bay and Delmarva coastal bays via digitization. COTE do not nest in other habitat types and therefore islands without beach or wetland were excluded (see Chapter 2 for further details).

A shapefile containing the centroid of all recorded historical and current COTE nesting colony sites was displayed within ArcMap 10.4 (ESRI, Redlands, CA) on top of the island polygon shapefile. Because of various restrictions with Landsat imagery (see Chapter 2), some smaller nesting colony sites were missed during the island image classification process. To select island polygons from the previously described shapefile at least one Landsat pixel in size (900 sq. m), a python script was developed to automate the process. To determine the accuracy of this selection process, the percentage of island polygons

correctly selected by the python script was calculated and compared across years (see Chapter 2). Islands missed by the python script (as a result of small size or similar spectral properties to surrounding water pixels) were considered incorrectly selected and were missing from analyses as a result. The percentage of nesting colony sites (both historic and current) selected by the python script was also calculated. Areas of these nesting colony sites from each imagery year were tabulated within Microsoft Excel 2013. Some nesting colony sites were correctly selected across all years while others were sporadically selected or, in some cases, never selected by the python script. To document consistent trends over time, a subset of islands correctly selected in 5+ imagery years was used. To determine the impact of individual nesting colony sites on total area, individual sites were removed from the total area summation and then added again to determine if the observed trends could be attributed to these sites or not.

To further determine if the overall trends in island habitat loss from the GIS analyses were correct, the nesting colony site centroid shapefile was displayed over Google Earth imagery. Using historical imagery, each nesting colony site was documented simply as present or not within the imagery across time. Historical imagery was not consistently available across all years of the study; therefore, the closest available year's imagery was used instead (imagery was on average two years behind).

Population trends:

An extensive database of all surveyed COTE nesting colony sites in Maryland was obtained from David Brinker of the Maryland Department of Natural Resources Natural Heritage

Program. This database contained breeding population numbers from all documented or suspected nesting colony sites obtained from yearly breeding colony surveys between 1985 and 2017 along with the geographic coordinates of all breeding colony centroids. Annual surveys were first initiated between the beginning of the COTE breeding season (early May) and before incubation began (once two to three eggs were laid). Researchers scouted both previously active and suspected nesting colony sites during this period and counted individual breeding pairs. Researchers then returned to the nesting colony sites at the height of the breeding season (late June to mid-July) and recounted the number of breeding pairs. This final number of maximum breeding pairs was documented in the aforementioned database. Years with incomplete survey efforts (1990, 1994, 1996, and 1998) were not included in any analysis. Unless otherwise stated, all population trends were determined using data from years when satellite imagery was also available (1986, 1991, 2006, 2011, and 2016) (1996 was an imagery year but as stated, was not included in any analyses). To determine if a correlation between total island habitat area and population numbers existed, a linear regression and Pearson's product-moment correlation were calculated within R 3.5.1 (R Core Team, Vienna, Austria).

RESULTS

Sixty-two nesting colony sites were surveyed in Maryland between 1985 and 2017 (Figure 3A). Using Google Earth imagery, all permanently lost nesting colony sites were determined to have experienced total habitat loss due to erosion or submersion. Two of the nesting colony sites (Hitech Project and North Point State Park pier) were not included in any analyses as they occurred on inland manmade structures. The largest number of

surveyed nesting colony sites that were active (where at least one breeding pair was recorded) in a single year was 18 in 1988 while the lowest number of active colonies (2) was observed in 2017. Fewer than half (41.9%) of all nesting colony sites were within the Delmarva coastal bays of Worchester County along the Eastern Shore of Maryland with the remaining colonies scattered throughout the Chesapeake Bay as far north as Baltimore County. Of the imagery years with complete surveying effort (1986, 1991, 2006, 2011, and 2016), both the lowest number of surveyed nesting colony sites (4) and the lowest number of surveyed breeding pairs within an active nesting colony site (349) occurred in 2011. An overall decline ($r = -0.97$, $p = 7.26 \times 10^{-3}$) in the number of surveyed breeding pairs was from 2,435 pairs in 1986 to 487 pairs in 2016, a decrease of 80%. A similar decline ($r = -0.93$, $p = 0.021$) was observed in the number of surveyed colonies (64.71%) across the same time period.

The python selected island polygons somewhat frequently failed to include COTE nesting colony sites (Table 3A). On average, colonies were accurately detected 38.3% across all years. Colony detection accuracy was highest in 1991 (45.6%) and lowest in 2006 (32.7%). Based on GIS analyses only, the number of total nesting colony sites declined by 31% over the thirty-year period. On average, 4.5 nesting colony sites were lost every 5 years; 13 nesting colony sites were lost between 1991 and 2006. In total, 35 nesting colony sites (55.6%) were never detected by the computer during image analysis as a result of their minute size (< 1800 m^2) and spectral similarities to surrounding land covers (see Chapter 2).

When considering each nesting colony site across time by using historical Google Earth imagery, a less drastic declining trend emerged. A decline of 15.8% in the number of total nesting colony sites was observed over the thirty-year period; an average of 1.8 nesting colony sites was lost every 5 years. Between 1991 and 2006, only 2 nesting colony sites were lost in the historical imagery as compared to 13 in the GIS analysis. Through extensive review of historical imagery, all nesting colony sites deemed "lost" had been completely eroded away. No nesting colony sites were fully or partially submerged.

Interesting trends emerged when analyzing changes in nesting colony site area over time (Table 3B). An increase in area was observed in both total nesting colony site area (all colonies across all years) (285.8%) and subset area (a summation from 12 nesting colony sites detected across 5+ imagery years; see Methods) (356.6%). A decline in subset area was observed between 1986 and 1991 (-8.9%). A sharp increase of 335.7% was observed between 1991 and 2006; an increase which can be completely attributed to the construction of the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island (hereafter Poplar Island) in the late 1990s. A slight decline in subset area was observed between 2006 and 2011 (16.9%) followed by an increase of 38.6% between 2011 and 2016. Nearly identical trends were observed in total nesting colony site area calculations as well (Table 3B). On average, subset area was greater than total area across all years (Table 3B). A significant correlation between total nesting colony site area and breeding population numbers was detected ($r = -0.94$, $p = 0.02$, $R^2 = 0.88$).

DISCUSSION

This study highlighted several intriguing trends regarding the COTE breeding population and number of nesting colony sites in Maryland over time. First, using a linear regression, this study effectively highlighted a steadily decreasing trend in both active nesting colony site and breeding pair numbers for COTE in Maryland from 1986 to 2016. Second, an anomaly was highlighted within the island polygons created during satellite image analysis: the marked increase in island habitat area between 1991 and 2006. Concurrently, a beneficial use project for dredged material (the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island) was developed in 1994 to rebuild the island over the original 1847 footprint. The documented increase in area was attributed entirely to the construction of Poplar Island in the late 1990s. This study is the first to effectively document the impact this single island has had on available island habitat in the region. Third, an overall increase in nesting colony site area was observed between 1986 and 2016 contrary to all previous assumptions regarding island loss and SLR.

Both breeding population size and number of nesting colony sites of COTE continue to decrease at an alarming rate regardless of available island area. Since 1986, the total breeding population of COTE in Maryland has declined by 80%. The number of active nesting colony sites experienced a similar decline of nearly 65% across the same time period. Annual fluctuations in breeding pair numbers do naturally occur within a given region (e.g. Maryland) (Figure 3B) but these fluctuations are unpredictable across years and make developing a deeper understanding of the breeding population difficult to ascertain in the short run. The number of active nesting colony sites has appeared to

stabilize at two sites (Poplar Island and Skimmer Island) since 2014 (Several smaller colonies (n = 4; number of breeding pairs totaling <350) fluctuated in number but ultimately failed and Jefferson Island, a well-established COTE nesting colony site since 2013, failed in 2017). Of these colonies, Poplar Island is overall the largest, averaging 365 ± 208.78 breeding pairs since 2003.

Both Poplar and Skimmer Islands are currently managed through partnerships between multiple federal and state agencies to ensure the continued survival of these islands in the future. Poplar Island's restoration is being led by the United States Army Corps of Engineers (USACE) and the Maryland Department of Transportation Maryland Port Administration (MDOT MPA) (Maryland Environmental Service, 2017). Skimmer Island has been managed primarily by the Maryland Department of Natural Resources, the Maryland Coastal Bays Program, and the Ocean City Fishing Center. Upon project completion at Poplar Island after 2040, half of the island is projected to be composed of upland habitat with the other half composed of wetland habitat. While COTE may nest in specific wetland habitat, the species composition of the wetland effectively determines if the habitat will be utilized by the species (Nisbet et al., 2017). The increasing trend in total island habitat area can also be attributed to the construction of Poplar Island. Construction of the island began in the late 1990s, directly in between two imagery years (1991 and 2006). In 2006, large portions of the island were not filled with material but by 2016, much of the island was filled with dredged materials. This contributed to the observed increase in area between 2011 and 2016. More recent sand deposition at Skimmer Island also contributed to this increase.

Recommendations/future directions:

This study highlighted the effectiveness of GIS analyses as well as the shortcomings of using lower-definition imagery datasets. The python code excelled at selecting larger islands but failed to detect minute islands (those roughly equal to one Landsat pixel (900 sq. m)) or islands with spectrally similar properties to the surrounding water. In fact, this python code was so ineffective at detecting these smaller islands that more than half of all nesting colony sites were missed by the code. This was especially the case in 1986 and 1991 where average colony size was well below 10 ha (7.72 ± 11.99 in 1986 and 5.45 ± 10.30 in 1991) due to numerous small nesting colony sites (n = 5) which were undetected by the Python code and eventually failed in later years. These small breeding colony sites are of critical importance to quantify when tracking habitat loss over time as even minute changes in available habitat area can have detrimental effects for the species. The smaller sample size of selected nesting colony sites greatly inflated the results by indicating that more colonies were lost per sampling period than the high definition imagery would suggest (4.5 nesting colony sites lost every 5 years vs. 1.8 nesting colony sites lost).

Should researchers wish to utilize this selection process technique again, higher definition imagery must be used. Using this imagery ensures that islands which may be impossible to detect in low definition imagery are not missed during the selection process. If islands are still not selected by the python code, a manual selection process may be necessary. Researchers would need to manually delineate nesting colony sites for each year of imagery

and then monitor changes in area across time. While time-consuming, this process would ensure that all observed trends in area accurately reflect reality.

Also as evidenced by this study, the supplementation of once natural islands through the deposition of dredged material has highly positive effects for COTE. The construction process for Poplar Island, including stockpiling of sand material, provides temporary attractive nesting material for COTE. Eventual habitat design (upland and wetland vegetated cells) will result in a conversion of habitat from open sandy sections to vegetated marsh not targeted for this species. However, island construction will continue through 2040, and during this process, will likely continue to provide attractive nesting habitat for COTE. Poplar Island also has designed "habitat islands" which include sand and shell substrate, targeted for ground-nesting terns, and with active management these islands are kept free of dense vegetation. Currently, three islands in the Chesapeake Bay are being supplemented with dredged material: Poplar and Hart-Miller Islands in Maryland and Craney Island in Virginia (Erwin et al., 2011). Two potential future sites for supplementation in Maryland are Barren and James Islands however the proximity of these islands to the mainland may ultimately promote mammalian colonization and therefore deter nesting waterbirds. Another potential site for supplementation of islands in Maryland is Tangier Sound which would be beneficial to COTE as many of the current islands are well removed from the mainland thus preventing mammalian colonization (Erwin et al., 2011). The construction of several small manmade islands in this region of the Bay would be provide additional breeding colony habitat for COTE. Proper management of these

islands to prevent vegetative succession and mammalian colonization would benefit nesting COTE.

In the 1980s, a shift occurred in public policy related to the use of dredged material in the construction of islands. This shift still greatly affects management decisions today and this may ultimately prevent the construction of newer islands in the Chesapeake Bay (Erwin et al., 2003). Poplar Island is just one example of how the use of dredged material can be beneficial to habitat design. As stated previously, the construction of this island has temporarily provided invaluable habitat for nesting COTE. Without dredged material, the restoration of Poplar Island may not have been possible and the breeding population of COTE in Maryland would have suffered greatly as a result. Future sites for dredged material are typically designated as Confined Disposal Facilities which are often diked, have tall steep sides, and tend to promote the colonization of *Phragmites australis*. This species grows prolifically and easily colonizes any open available habitat thus forcing ground nesting waterbird species like COTE to find alternative breeding sites (Soots & Landin, 1978).

While island loss and its impact on nesting waterbird populations have been well documented, much is still unknown regarding certain aspects of the Chesapeake Bay ecosystem and their impacts on breeding COTE. Commercial fisheries are one of the main economic drivers in the region but the impact of this industry on COTE is still poorly understood. Runoff into the Chesapeake Bay containing newly created chemicals may also have lasting consequences and impacts on COTE that have yet to be fully understood

(Erwin et al., 2011). In order to provide effective recommendations for managers, these large data gaps must be fully addressed and understood in the near future as the looming threat of climate change continues to negatively impact the region.

4. ASSESSING NEST ATTENTIVENESS OF MARYLAND STATE-ENDANGERED COMMON TERNS (*Sterna hirundo*) USING TEMPERATURE LOGGERS AND VIDEO

INTRODUCTION

A key measurement of avian reproductive success is nest attentiveness, defined as the time at least one adult is present on the nest (Nisbet et al., 2017). Inherently, there are two possible statuses when examining nest attentiveness: the consecutive period of time the adult remains on the nest (referred to as an on-bout) and the time in which the nest is unattended, called an off-bout. Unlike a majority of species, both sexes of common terns (*Sterna hirundo*) (hereafter COTE) incubate the eggs, with females incubating slightly more than males during the daytime hours. However, male nest attendance drops to <10% during nocturnal hours (Nisbet et al., 2017). Incubation stints by either parent typically last between <1 min to several hours in duration, with nest attentiveness typically highest during cold precipitation events or midday heat (Nisbet et al., 2017).

One critical factor that influences nest attentiveness is the presence of predators within the breeding colony. COTE respond to predators in two different ways, each of which exposes nests to predation and weather and decreases nest attentiveness. First, adults can aggressively mob predators that threaten eggs or chicks until the predator eventually leaves the colony or moves away from the nest (Burger & Gochfeld, 1991; Meehan & Nisbet,

2002). Second, adults may form large evasive flying flocks composed of numerous individuals (also known as “dreads”, “panics”, or “formation flights”) when they recognize that a threat is present (Meehan & Nisbet, 2002). This behavior may last anywhere from <1 min to several hours even when the perceived predator is not a direct threat to eggs or chicks. Leaving the nest for such long periods of time can have detrimental effects on reproductive success, exposing eggs to the sun or cold temperatures which can slow or stop embryonic development (Nisbet, 1975; Meehan & Nisbet, 2002). This exposure may also leave nests vulnerable to smaller predators such as black-crowned night herons (*Nycticorax nycticorax*) that are normally forced away by adult mobbing (Nisbet & Welton, 1984). This is highlighted by increased predation and egg mortality observed in nests which exhibit flocking behavior for greater than normal durations.

In addition to predation, adults must also attempt to limit the exposure of their nest to extreme weather conditions. At extreme high temperatures, even short exposure can impede proper egg development. During extended periods of high temperatures, adult COTE may leave the nest, soak their bellies and feet in water, and return to the nest to cool their eggs. This soaking can have several functions including cooling the adult, cooling the eggs, increasing the amount of water available for young chicks to drink (if eggs already hatched), and increasing nest humidity (Grant, 1981). Larger chicks (between 9 and 17 days (d) old) tend to hide in clumps of vegetation and only leave cover to move to other vegetation or to their parents (Nisbet, 1983). Nisbet (1983) reported that, during a day with temperatures upwards of 35°C, 13 out of 15 chicks older than 10 d died. Much like with foraging, adults have a cost-benefit relationship between cooling themselves and cooling

their eggs and young. Exposing the eggs and chicks in any situation is detrimental but this is particularly true at higher temperatures.

Proximity to food sources and prey availability can also affect nest attentiveness rates. The availability of food leads to a tradeoff between incubation and foraging in which adults must balance foraging for themselves with incubating their eggs (Martin, 1987; Matysiokova & Remees, 2010). The more time adults spend incubating eggs, the shorter overall time required before the eggs hatch and the less time they are vulnerable to predation or the elements. Conversely, if adults must expend more time foraging the incubation period is extended, and the risk period of exposure is prolonged. One study found that, on average, foraging trips by COTE adults to feed their young were 17.2 min and that an estimated 42 to 64% of daylight hours (between 7 and 10 h) were spent foraging (Courtney & Blokpoel, 1979). The observed increase in foraging time correlated with an increase in the brood size from one to four chicks. With this extended duration away from the nest, both eggs and chicks were more exposed to predators and overall nesting success could be compromised (Martin, 1987).

Unfortunately, while general trends in COTE nest attentiveness are well documented, the fine scale detail required to truly understand how these behavioral tradeoffs express themselves in the wild population is lacking. Currently, no quantitative data exists about incubation duration and time of day. Fortunately, advancements in video technology in recent decades have made video monitoring of wildlife more cost effective and accessible. A wide variety of applications exist for remote monitoring of numerous wildlife behaviors

ranging from mammal movement ecology (Stewart et al., 1997;Kleist et al., 2007; Huckschlag, 2008), raptor foraging and breeding ecology (Rogers et al., 2005; Reif & Tornberg, 2006; Jacobs & Rothe, 2011), to nekton migration and movement ecology (Kimball & Able, 2012; Spampinato et al., 2014; Bouchet & Meeuwig, 2015). Furthermore, the miniaturization of video monitoring components in recent decades has made this technology more applicable for studying avian breeding ecology directly at the nest site (Sabine et al., 2005; Friesen et al., 2013; Gill et al., 2015; Vasseur & Leberg, 2016; Mosbech et al., 2017). With the implementation of this new technology, however, come previously unforeseen issues.

A meta-analysis of numerous papers (n = 19) using video monitoring techniques to research breeding ecology of avian species (see Table 1 in Richardson et al., 2009) highlights the effects this technology may have on breeding success. Richardson et al. (2009) reports dramatically conflicting effects of video monitoring on reproductive success. While, one study (Schaefer, 2004) found that nesting success was higher for nests monitored by cameras as compared to those that were not, five other studies found nest abandonment to occur when cameras were deployed early in the nesting cycle. However, this effect was greatly reduced after the deployment technique was altered and cameras were installed later in the season (Richardson et al., 2009). Richardson et al. (2009) also reported a significant positive effect of cameras on daily nest survival estimates, with a significant positive effect on nest survival observed in studies where cameras were used in the same site for <2 years. A non-significant positive effect was also observed in studies conducted in open habitats (Richardson et al., 2009).

Richardson et al. (2009) proposed that increases in reproductive success may be the result of some predators (e.g. mice (*Muridae*)) avoiding novel objects placed at the nests. However, as study length increases this effect may diminish or reverse as predators may begin associating cameras with active nests due to placement of flags or similar markings at the nest or perhaps even repeated researcher behavior. Renfrew and Ribic (2003) recommend that researchers avoid long-term camera exposure in a single area in order to prevent such habituation.

One promising technological advancement for examining avian reproductive ecology is the use of the temperature loggers commonly referred to as iButtons (Maxim Integrated, San Jose, CA). Multiple studies have used temperature loggers to quantify incubation behavior and nest attentiveness rates (Hartman & Oring, 2006; Schneider & McWilliams, 2007; Zangmeister et al., 2009; Sutti & Strong, 2014; Walters et al., 2016; Bueno-Enciso et al., 2017). This technology has been utilized to a high degree of accuracy and precision providing researchers with information that may have otherwise been highly disruptive to obtain. However, previous work has highlighted many shortcomings with such devices. For instance, whenever possible iButtons should not be placed into nest structures that would be damaged during installation. Sutti and Strong (2014) also mention that, for remote study sites, continuous recording of nest temperature throughout the nesting season is impractical due to the limited storage capacity of iButtons. Finally, iButtons are unable to detect off-bouts shorter than the duration of the sampling interval due to an inherent lag

in detection (Walters et al., 2016). Continued research is required to fully understand the utility of iButtons or other similar temperature loggers to the study of nest attentiveness.

The need for fine scale data regarding COTE nest attentiveness has paved the way for a comprehensive examination of this behavior via a pairing of video surveillance technology with temperature loggers. The objective of this study was to characterize nest attentiveness in COTE while also exploring the ability of both remote video monitoring and temperature logging devices to be used to gather such data independently and as part of a paired system. The specific objectives were to: (1) quantify nest attentiveness rates and nesting behaviors displayed by COTE and determine how these may relate to the reproductive success of the observed colonies, (2) examine the practicality of remote video data collection on COTE nests for reproductive monitoring, and (3) evaluate the ability of data collected via temperature loggers to determine nest attentiveness by comparing these data to paired video evidence.

METHODS

Study area:

This study was conducted on the two known long-term active breeding colonies of COTE in Maryland. The first of our two sites was the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island (38°45'42.1668"N, 76°23'3.2958"W) (hereafter Poplar), a beneficial use project developed in partnership between the U.S. Army Corps of Engineers and the Maryland Department of Transportation Maryland Port Administration (Maryland Environmental Service, 2017). This island is located in the Maryland portion of the

Chesapeake Bay and is composed entirely of cleaned dredged material from the navigational channels leading to the Port of Baltimore. Originally inhabited in the 1800s, the island was reduced to only 1.62 ha in size due to extensive erosion; but the restoration project has rebuilt the island in its original footprint. Upon projected completion in the late 2030s, the western half of the island will be upland habitat and the eastern half will be saltmarsh (Maryland Environmental Service, 2017).

The breeding population of COTE on Poplar has historically been the highest, on average, in the state. Breeding numbers have fluctuated heavily over time with a peak of 827 breeding pairs in 2003. While the number of breeding pairs steadily declined to only 86 breeding pairs in 2016, the colony appears to be rebounding with 254 breeding pairs documented in 2017.

The second study location was Skimmer Island (38°20'11.6946"N, 75°5'39.5448"W) (hereafter Skimmer), a small uninhabited island in the Isle of Wight Bay along the Atlantic seaboard. The island has been an important nesting site for black skimmers (*Rynchops niger*), royal terns (*Thalasseus maximus*), and COTE in recent decades but has been slowly eroded by waves and boat wake action in recent years (Maryland Department of Natural Resources, 2016). Since 2009, the Maryland Coastal Bays Program (MCBP), Maryland Department of Natural Resources (MD DNR), and Ocean City Fishing Center have developed a partnership to help conserve the island through annual deposition of dredged sand on the island. In 2015, MD DNR and MCBP issued a no wake zone around the island

to prevent further degradation and promote the return of breeding population of aforementioned species (MD DNR, 2016).

First monitored in 1989, the COTE breeding population on Skimmer experienced a peak of 524 breeding pairs in 1995 before complete colony collapse in 2005 due to habitat loss from erosion. In 2009, the colony was active once more until 2012 when extensive predation by great horned owls (GHOW) (*Bubo virginianus*) contributed to another collapse. The colony became active for a third time in 2016 (54 recorded breeding pairs) and has remained active since.

Surveillance system construction:

A pilot project was conducted in April 2016 to test multiple models of video cameras and digital video recorders (DVRs). The video surveillance system used for the pilot project consisted of both an indoor-outdoor wired (Lorex® LBV2711B) and wireless (Lorex® LW3211) camera (both models had an environmental rating of IP66) and a compatible 8-channel DVR model (Lorex® DV7041 for a wired system or Lorex® DV708 for a wireless system) used in concert with iButtons.

Picture quality, the farthest possible distance cameras may be placed from the DVR without picture loss, and equipment set up were all tested during this pilot project. Though the limited quality and quantity of data gathered in 2016 rendered this data unusable for assessing nest attentiveness, the results for this initial work, along with the need to address

power consumption issues, resulted in the final surveillance system design utilized in 2017 (see Wall et al. (2018) for details).

Once methods were finalized, video surveillance systems were installed at colonies on both Poplar and Skimmer Islands. Six cameras were placed in each colony, and each camera was connected to the same eight channel DVR. On Poplar, the wireless receivers for these cameras were secured to the wall of the container housing the DVR. On Skimmer, receivers were secured to 3 m tall PVC pipes to provide a clear line of sight between the receivers and cameras over tall vegetation. At each site, five of the cameras were placed at individual nests and one camera was placed at the edge of the colony facing the length of the colony for overall predator detection. Cameras were scattered in order to provide an overall view of the entire colony. The five nest cameras were secured to 0.5 m tall 2 in. x 4 in. boards cut to a point at one end that were hammered into the ground roughly 0.5 m away from the edge of the nest scrape. A single camera was placed at one end of the nesting colony at a height of 1.5 m facing the entire length of the colony. This camera was secured to a 1.75 m 2 in. x 4 in. board cut with a point at one end that was hammered into the ground. Initially, it was believed that these elevated cameras may be used as perches for predators and as such, should not be used in the colonies. However, during visits to the colonies, researchers only observed the elevated camera being used as a perch by COTE. It is unclear whether this is the case when researchers were away from the colony, but video review did not indicate use by predators ever occurred. In an effort to ensure this camera would not be used as a perch by potential predators, bird spikes were secured to the post and camera using zip ties.

Cameras were placed in both colonies once a majority of nests in the colony contained at least two eggs. This ensured that adults would become acclimated to the cameras before the initiation of incubation and a complete clutch of three eggs is laid. Video was recorded continuously from a 78º field of view in 720p resolution at a frame rate of 25 fps. The camera's built-in IR light, composed of 18 LEDs, was able to record video at a minimum illumination of 0 lux up to a distance of 27 m. Data was collected during traditional nest surveys (twice or thrice weekly on Poplar and once weekly on Skimmer) by disconnecting the 1 Tb hard drive and replacing it with an empty drive of the same capacity. If not replaced, hard drives would typically become completely filled within 1.5 weeks.

Video review:

In order to review video, the hard drive from the field DVR needed to be removed and placed into an in-lab DVR for processing. The in-lab DVR was the same exact model as the field DVR. For reviewing video, one channel was observed at a time. A total of six channels were recorded on each hard drive: one for each nest camera and one for the elevated colony camera. Video was reviewed at four times normal speed during review and each nest was reviewed in 24 hr periods. Once an entire channel was reviewed, the reviewer proceeded to the following channel and repeated the process.

Video reviewers documented each time an adult left and returned to the nest to the nearest minute, the duration of nest vacancy, and the duration of nest attendance. This resulted in a data file that listed the status of the nest, with adult on or off of the nest, at every one-

minute interval for which video existed. If possible, the reason for the adult's departure (foraging, predator present, belly soaking, or unknown) was documented as well. Behaviors at the nest were opportunistically documented during review which included mate switching (mates switching incubation duties at the nest), mating (copulation at or near the nest), flocking (entire colony or large portion is flushed from their nests by some disturbance), nest maintenance (mate adds or removes nest material from the nest), surrounding nest maintenance (mate off nest moves sticks or stones with beak in the area surrounding the nest; typically seen in concert with mate switching), chick feeding (adult feeds a chick), and fish in mouth (adult returns to nest with a chick in its mouth to consume or present to a mate/chick). Initially, it was thought that feeding rates could be determined through this behavior cataloguing but due to lost video, these rates could not be accurately calculated (see Discussion). Finally, when reviewing colony camera video, reviewers noted the number of times adults flocked and the cause for the flocking. The limited range of IR lights prevented review of colony camera video between 2200 and 0400 nightly at both colonies.

Video backup and data management:

Lorex® branded DVRs provide users with the ability to backup video utilizing a thumb or external hard drive or via free cloud-based client software (FLIR Cloud ™). If using an external drive, video may be backed up directly in either DAV (a Lorex® proprietary file format) or ASF (a standard video format playable in numerous media players) format. Individual video files were heavily partitioned and ranged in size from 1 s to 5 min in duration. The number of files available and time required for backup were dependent on

the partitioning of these videos. Between ~100 to >250 files could be backed up at once and require upwards of 4 hr to complete. If backing up video via the client software, the DVR must be connected to a router which is in turn connected wirelessly to a computer running the software; these devices do not need to be on the same network in order to connect. Once connected, video was played back and clips of this video were created and directly downloaded to the computer's hard drive. Clip duration, which ranged from <30 s to 24 hr, determined the file backup time.

iButton placement and data collection:

Thermochron® iButtons (model nos. DS1921G, DS1921H, DS1922L; Maxim Integrated, San Jose, CA) (hereafter iButtons) were attached to 15 cm plastic tent stakes using Velcro® and placed into a ring of craft foam with a hole cut in the center matching the dimensions of the iButton. This foam was used to prevent the iButtons from damaging eggs as they were being rotated by the incubating adult, and was also secured to the tent stakes via Velcro®. iButtons were placed in the center of nests flush with the nesting substrate. These methods are a minor modification of those described by Hartman and Oring (2006) during their 2005 field season.

iButtons were placed throughout both colonies in a subsample of active nests containing two or more eggs (37 on Poplar and 39 on Skimmer) as COTE begin regularly incubating the nest after two or more eggs have been laid (Nisbet & Cohen, 1975; Nisbet et al., 2017). The sampling interval (time in between when each temperature reading is taken) was set to 3 min due to the built-in lag time in these devices (pers. comm. Maxim Integrated, San

Jose, CA). A balance between battery life and available storage must be taken into account when determining sampling interval duration. Shorter intervals exhaust the internal storage faster than longer intervals whereas longer intervals put greater strain on the battery life as the loggers are gathering data over a longer duration. Depending on both the sampling interval duration and the environmental temperature in which the iButtons are used, internal storage life ranges from several days to several months and battery life ranges from one to ten years. All nests monitored by video cameras had iButtons (n = 10), ensuring that video could be compared with the iButton data and allow for validation of nest attentiveness (see "Video review"). The iButtons paired with cameras were placed near one another to facilitate powering of the cameras. The remaining iButtons were placed throughout both colonies.

In order to access the temperature data on the iButtons, a Blue Dot™ Receptor 1-Wire Network Cable (model no. DS1402D-DR8; Maxim Integrated, San Jose, CA) was connected to a USB port adaptor (model no. DS9490R; Maxim Integrated, San Jose, CA) and then was connected to a laptop. This receptor was used to not only collect data but also to program "missions" or extended periods of time in which the iButtons were actively collecting temperature data. The iButtons were placed securely into the receptor and the data was gathered as a text file and converted to CSV format.

iButton temperature data was then interpolated for each minute based on the recorded temperature data through use of the "na.interpolation" function within R. For occasional

data gaps between temperature readings longer than five minutes due to improper iButton calibration), iButton data was not interpolated.

Weather station data:

Data gathered by the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information was used to approximate weather conditions on Poplar and Skimmer Islands (NOAA, 2018). Local climatological data (temperature, collected in ~20 min increments, and barometric pressure, collected in ~60 min increments) were gathered from two municipal airports within 10 km of each breeding colony (station IDs WBAN:00124 (38°58'1.2"N, 76°19'58.8"W) and WBAN:93786 (38°18'29.99"N, 75°7'26"W)) from 1 June to 31 July, 2017. While efforts were made to collect data directly at the study sites, complications with in-colony weather stations resulted in lost or unusable data and required the use of external data sources. Following the collection of weather data, ambient temperature and barometric pressure were interpolated for each one-minute data point for periods between recorded observations of less than 59 minutes in length using the same method as described for the interpolation of iButton data.

Defining time of day bins:

Once ambient temperature data was gathered for both colonies, time-of-day bins were defined. Each 24-hour period was split into four distinct time of day bins: Morning, Peak, Cooling, and Night (Tables 4A and 4B). The Night bin was defined first. Sunrise and sunset times were determined for both colonies across the entire study period (1 June to 31 July) using the United States Naval Observatory (USNO) sun and moon rise/set tables (USNO,

2016). The Night bin was delimited by general times before which all sunrises and after which all sunsets occurred. The end time for the Night bin was designated the start time for the Morning bin. The end time for the Morning bin was the start bin for the Peak bin.

Defining the Peak bin required a multi-step process. The peak ambient temperature for each 24-hour period was determined in Microsoft Excel 2013 using the MAX formula. The time which corresponded to this peak was also determined. Occasionally, peak temperature was reached multiple times ($n < 5$) in the span of several hours. If this occurred, all these times were noted as well. Peak temperature was identified for every single day and then averaged by month. The averages for June and July were compared and the Peak bin start time was defined by the earlier of the two average times. Selecting this bin start time ensured that the majority (>95%) of all peak times would be included within this bin; cooling days were the only notable exception to this. Once peak temperature was defined, the time in which temperatures began cooling was determined. This typically occurred within an hour of when peak temperature was recorded and, as a result, an hour cut-off was used as the Peak bin end time. Much like the Morning bin, the Cooling bin was delineated by the Peak and Night bins. The start time for the Cooling bin was the end time for the Peak bin and the end time for the Cooling bin was the start time for the Night bin. Table 4A highlights the start and end times for each bin for both breeding colonies. Each one-minute record was then placed into one of the time-of-day bins.

Natural bout identification:

Bouts, or consecutive periods of time in which an adult was present at the nest or not, were first identified based on the video review that gave a status of on or off for each one-minute increment. These status determinations were assumed to accurately reflect in-colony conditions and therefore were taken as truth. A script was then built within R 3.5.1 (R Core Team, 2018) that identified every on and off bout within the dataset. The minimum consecutive length of time required to be labelled a bout was one minute, as this was the precision with which data was recorded. In order to appropriately characterize nest attentiveness bouts before or after periods when video was not recorded or was not viable were discarded since one could not accurately confirm the actual duration of the bout. Similarly, bouts at the beginning or end of the entire sampling period, bouts which occurred during more than one time-of-day bin, and bouts immediately prior and following in-colony researcher presence were discarded. This approach was designed to provide a basic understanding of nest attentiveness rates while also providing researchers with a general description of how adults behaved naturally outside of any in-colony disturbance.

The duration of each bout was calculated and this value assigned to each one-minute interval by bout. Bout duration was calculated without respect for time of day as there is no biological reason to expect these behaviors to fall smoothly within the artificially created bins. However, summary statistics of the iButton data associated with each nest (average, minimum value, maximum value, and variance) were calculated within R for bout duration by bin, with bouts spanning more than one bin split accordingly. All calculations took place within R.

Prediction of bouts based on iButton and weather data:

iButton bouts were identified in the same fashion as natural bouts with the following exceptions: (1) bouts which occurred when researchers were within the colony were similarly discarded but bouts before or following research presence were not discarded and (2) bouts before video data went out of range were retained. iButton off-bout duration was calculated within R following the methods described for natural bouts.

A suite of six a priori models were run against a data subset such that each record had a value for all covariates used in the most complex model. This was completed to ensure that sample size would not change between models and invalidate AIC comparison (Konishi & Kitagawa, 2008). All models were run by time of day bin and compared based on AIC score (Konishi & Kitagawa, 2008).

After best fit models were selected for each time-of-day bin, the data was further split into training (25%) and testing (75%) subsets via a stratified random sampling of the on vs off iButton bouts. The training subsets were then used to inform the previously determined best fit models. Following model fitting, the "predict" function in R was used to determine the predicted probability of each record in the testing dataset being part of an on-bout. All points with a predicted probability of the bird being on the nest <0.5 were considered off while the remainder were classified as on. This status was then compared to the status assigned via video classification (assumed as truth) and the percentage of data correctly

predicted was calculated by probability bins and by the duration of the bout with which each record was associated.

Finally, a logistic regression was run to determine if bout duration or location of the point within a bout (i.e. within the first 5 minutes or not) impacted the likelihood of a given data point being correctly predicted. The beta estimates from this regression were then exponentiated to determine the comparative odds of successful prediction.

RESULTS

Video:

A total of 13 nests were monitored with video cameras (8 on Poplar and 5 on Skimmer). Three of the nests on Poplar failed within 3 days of camera deployment. The cause of this failure was due to nest wash-out from heavy storms and subsequent nest abandonment. This equipment was subsequently relocated to other active nests. A total of 3,802 h of video were collected in 2017. Of this video, 1,765 h were out of range leaving 2,037 h of useable video. Video was deemed out of range if video was recorded but power was depleted at the camera and the connection to the DVR was temporarily lost or the wireless signal was interrupted or blocked by vegetation. When this occurred, an all-black screen with a message reading “Out of Range” was displayed. An additional 5,365 h of video were lost due to various issues detailed in the Discussion section.

Review of colony camera video revealed a trend regarding the initiation of flocking events. For both Poplar and Skimmer, most flocking events were initiated during the Cooling bin

(62.22%, n = 196) while few were initiated during the Night bin (15.56%, n = 49). An equal number of flocking events occurred in the Morning and Peak bins ($\overline{x}$ = 35) (Figure 4A).

A total of 714 behavior events were documented during review of video (Figure 4B). Mate switching comprised the majority (67.65%, n = 483) of documented behavior events with flocking being the second most documented behavior (19.19%, n = 137). Nest maintenance and surrounding nest maintenance comprised roughly 10% (n = 67) of all observed behaviors. Chick feeding and fish in mouth comprised approximately 3% (n = 24) of all documented behaviors. Nest defense was the least documented behavior comprising only 0.42% (n = 3) of all observations. Mating was never documented during video review (see Discussion).

Several disturbances were documented in the video, all of which occurred on Skimmer. In every instance, nests were temporarily abandoned while the disturbance was present in the colony. Domestic dogs (*Canis lupus familiaris*) were observed walking among nests on 11 June and 23 June 2017. Fishermen were observed walking along the edge of the colony twice on 6 June 2017. GHOW, a key nocturnal predator of COTE, were detected at individual nests on nine separate instances. In one instance, a GHOW was seen predating a chick near the nest.

iButtons:

A total of 76 nests were monitored with iButtons (37 on Poplar and 39 on Skimmer) over the course of the 2017 season. Of these iButtons, four were lost on Poplar and five were lost on Skimmer due to nest wash-out, removal by parent, or another unknown reason. When conducting nesting surveys, 18 iButtons (8 on Poplar and 10 on Skimmer) were discovered buried under nesting substrate. Poplar iButtons were buried 3.18 cm on average whereas Skimmer iButtons were buried 1.39 cm on average. All of the data presented in this study came from iButtons that were not buried under sand and came in contact with the surface of the nest (n = 58). Foam rings surrounding iButtons were removed from nests on five occasions (four on Poplar and one on Skimmer). Suspected egg damage from iButtons was documented once on Poplar and 11 times on Skimmer. Of these damaged eggs, only the Poplar egg hatched; all Skimmer eggs were depredated by GHOW (see "Video" below). The mean number of deployment days on Poplar was 25.08 d whereas the mean number of deployment days on Skimmer was 24.97 d. For Poplar, a mean of 9.03 d of data were lost due to filled internal storage capacity. Skimmer iButtons had only 2.23 d of lost data.

Natural bouts from video:

The time-of-day bin definitions proved highly successful and illustrated expected daily temperature trends: temperatures were lowest during the Night bin, rose during the Morning bin, were highest during the Peak bin, and steadily declined during the Cooling bin. On Poplar, bout temperature followed expected trends. During the Morning bin, off-bout temperature was higher on average than on-bout temperature as adults left the nest

completely exposed to direct sunlight and the radiating heat of the surrounding sand. Similarly, average Peak temperature was warmer during off-bouts than on-bouts. During both the Cooling and Night bins, mean temperature was greater during on-bouts due to the insulating properties of the incubating adults on the nest. Similar trends were also observed on Skimmer Island. Both mean Morning and Peak off-bout temperature was higher than on-bout temperature. On Skimmer, during the Cooling bin, average nest temperature during on-bouts was lower than during off-bouts. Much like Poplar, on-bouts during the Night bin on Skimmer were warmer than off-bouts due to the insulating properties of the incubating adults.

The number and duration of natural bouts varied greatly by nest at both Poplar and Skimmer (Tables 4C and 4D). On average, on-bouts were longer in duration than off-bouts at both Poplar and Skimmer. On Poplar, average on-bout duration per nest ranged from 34 to 213 min whereas average off-bout duration per nest ranged from 3 to 26 min. Skimmer off-bout duration was, on average, longer than Poplar Island off-bouts, ranging from 28 to 40 min. Skimmer on-bout duration, however, had a larger average range from 52 to 187 min in length.

For natural bouts, minimum, maximum, and average temperature and temperature variance were all highly variable across bins and colonies (Tables 4E and 4F). Of Poplar on-bouts, the highest average minimum temperature occurred during the Cooling bin (35.56ºC) while the lowest average minimum temperature occurred during the Morning bin (31.17ºC). Unlike on-bouts, minimum temperature during Poplar off-bouts was, on average, highest

during the Peak bin (36.12ºC) and lowest during the Night bin (31.16ºC). Regarding both Skimmer on- and off-bouts, the highest average minimum temperature occurred during the Peak bin (31.98ºC (on-bout); 34.43ºC (off-bout)) while the lowest average minimum temperature occurred during the Night bin (23.65ºC (on-bout); 21.94ºC (off-bout)). Maximum temperature was highest during Peak on-bouts on both Poplar (36.24ºC) and Skimmer (34.95ºC). Off-bout maximum temperature was highest during the Peak bin as well at both colonies (36.22ºC on Poplar and 34.88ºC on Skimmer) (Tables 4E and 4F). During on-bouts at both colonies, the highest average temperature occurred during the Peak bin while the lowest average temperature occurred during the Night bin. For off-bouts, the same trend was observed. Temperature variance differed greatly between both colonies but generally was higher at Skimmer (Tables 4E and 4F).

Model selection and predicted bouts:

For Poplar, the most complex model was found to be the best fit for the Peak, Cooling, and Night bins; though the Morning bin required a model without the interaction between interpolated iButton and ambient NOAA temperature readings (Tables 4G and 4I). The Morning bin model differed from the most complex model by only two AIC points effectively indicating no real difference between the two. The most complex predictive model was used for all Skimmer time-of-day bins (Table 4H and 4J). At both colonies, these models were only effective at predicting bout status when a bout occurred during the Night bin. In all other time-of-day bins, models predicted nearly every bout status as on. While on-bouts were correctly predicted with high accuracy during the cooling period, off-bouts were not well recognized by this approach, with only a 25% success rate at Poplar

and 50% success rate at Skimmer. For Poplar, 81.58% of Night bin bout status was correctly predicted by the model. At Skimmer, the model was slightly less successful (78.39% of bout statuses correctly predicted).

When determining predictive success of the best fit models by bout duration, the only time-of-day bin to make reliable predictions was the Night bin (Tables 4K and 4L). At both Poplar and Skimmer, the percentage of correctly predicted on-bouts increased as bout duration increased while no trend in the predictability of off-bouts was observed. For Poplar off-bouts, the model was able to correctly predict all off-bouts less than four min in duration in both the Cooling and Night bins, though there were very few such data points (n =12). Outside of this duration bin, the model most accurately predicted Night bin off-bouts with a duration greater than 60 minutes (69.79%). Much like Poplar, the Skimmer model was able to correctly predict 66.67% of all Cooling bin off-bouts four minutes or less in duration. During the Night bin, the model accurately predicted 81.32% of all off-bouts longer than 60 minutes in duration. Overall, the Night bin model for Poplar was slightly more accurate than the Skimmer model for bouts over 60 min in duration (cumulatively 84.25% vs. 80.91% of bouts were correctly predicted) (Tables 4K and 4L).

The impact of bout duration on predictive success varied greatly between Poplar and Skimmer. On Poplar, the likelihood of correctly predicting attentiveness status ranged from 1.0004 (Night) to 1.091 (Morning) ($p < 0.001$ for all bins) times as likely for each one-minute increase in bout duration. Meanwhile points after the first five min of a bout ranged from 1.394 ($p = 0.015$; Morning bin) to 3.979 ($p < 0.001$; Night bin) times as likely to be

correctly predicted. Like Poplar, the likelihood of correctly predicting attentiveness status on Skimmer ranged from 1.0004 ($p < 0.001$; Night bin) to 1.091 ($p < 0.001$; Morning bin). However, the likelihood of accurately predicting status outside the first five minutes of a bout was much higher on Skimmer ranging from 6.682 (Cooling) to 11.846 (Peak) times as likely to be correctly predicted.

DISCUSSION

Video observations:

Video monitoring of nests proved to be an effective technique for measuring nest attentiveness rates and monitoring nesting behaviors. Despite large gaps in coverage from lost or out of range video, it was still possible to document multiple nesting behaviors and to categorize nest attentiveness via what was believed to be biologically relevant bouts.

Overall, video cameras were deployed at nests for a large portion of the nesting period. As mentioned previously, three nests on Poplar failed within 3 d of camera deployment. These failures were not due to the placement of cameras at the nest but were instead due to wash-out of nests from heavy rain storms and subsequent nest abandonment. All other cameras on Poplar were deployed for the entirety of the incubation period (+21 d). Skimmer cameras were deployed for nearly 2.5 times the duration of Poplar cameras primarily due to the observed extended incubation period of +30 d. None of the camera nests hatched indicating that adults were incubating nonviable eggs. When a nocturnal predator (e.g. GHOW) was detected within the colony, incubating adults flushed from their nests, did not

return until dawn which caused internal egg temperature to drop to fatal levels, and upon their return, continued incubating these nonviable eggs.

As evidenced by video review, adults on Skimmer Island abandoned the nest nightly as a result of GHOW presence only to return the following morning. This extended period away from the nest greatly extended the incubation period thus the monitoring duration for these nests was much greater than that on Poplar. Colonial nighttime desertion has been well documented (Nisbet & Welton, 1984; Hébert, 1985) for colonies where GHOW predation is prevalent as it has been on Skimmer for a number of years (pers. comm. David Brinker). The duration of this desertion, which may last from several minutes to overnight (as was the case on Skimmer), is dependent on the stage of the nesting cycle, proximity of the owl to the breeding colony, and the activity level of the owl (Arnold et al., 2006).

The inclusion of an elevated colony camera provided researchers with an overall view of the colony. At both colonies, most flocking events occurred during the Peak and Cooling bins. The reason for these flocking events could not be determined through careful review of video but it is not unusual for COTE to flock when no stressors are present (Nisbet et al., 2017). Cullen (1956) posited that these events are best interpreted as false alarms resulting from individuals' fear of potential land predators entering the colony as well as the species' overall tendency to abruptly respond to sudden movements at neighboring nests. Researchers have documented this behavior occurring throughout the breeding season with decreasing frequency as the season progresses (Cullen, 1956; Morris & Wiggins, 1986).

Review of all observed nesting behaviors did not produce any unknown or previously undocumented nesting behaviors. Predation by GHOW and anthropogenic disturbances were the only documented known stressors for nesting COTE. The most documented behavior, mate switching, is very well understood and has been documented by multiple researchers (Wiggins & Morris, 1987; Nisbet et al., 2017). Unfortunately, chick feeding rates could not be determined from the video, with only 13 instances of chick feeding being documented across both colonies. These observations were too infrequent for an accurate calculation of chick feeding rate over time. This lack of data was not unexpected as cameras were deployed around the beginning of chick feeding. Mating was never documented because most copulation events occur between 10 d prior to laying of the first egg to 2 d after (Cullen, 1956; Morris & Wiggins, 1986; Wiggins & Morris, 1986; Nisbet et al., 2017), well before cameras and temperature loggers were placed in the colonies.

iButton observations:

iButton temperature loggers proved to be a partially effective means of documenting nest attentiveness of COTE. Occasionally, loggers became buried beneath the sand and were unable to accurately log temperature readings of incubating adults or eggs. Such altered results were observed even when iButtons were covered by <1 cm of substrate. This only occurred in non-camera monitored nests and as such did not impact any of the results presented in this study. iButtons which could not be located were believed to have been removed from the nest by incubating adults. Due to the built-in lag time between temperature readings of 180 s, iButtons could not accurately detect off-bouts less than this

sampling period. This lag time may explain why model predictive success was particularly low for shorter bouts (<30 min) especially for Poplar (Tables 4K and 4L). See Study Limitations for an in-depth discussion of these issues.

iButtons placed on Skimmer fared much better than those on Poplar. More than half (51.35%) of Poplar iButtons had >10 d of lost data whereas only a single iButton on Skimmer lost this much data (14 d). The cause of this difference in effectiveness is unknown but it may be due to filled internal iButton storage. This occasionally occurred due to the inability to access the colonies by boat as a result of poor weather conditions (e.g. rain and high winds). Filled iButton storage occurred in 39.4% (n = 37) of all Poplar iButtons and none of Skimmer iButtons across the study period.

Roughly equal numbers of iButtons were lost at each colony due to nest wash-out from heavy storms, suspected removal of the loggers by nesting adults, or other unknown reasons (8 on Poplar and 10 on Skimmer). As mentioned previously, on several occasions at both colonies, iButtons were found buried in sand leading to highly inaccurate data. Accurate temperature readings were only possible if the iButton came in direct contact with the incubating adult or the air space within the nest.

Natural bouts from video:

Quantifying natural bouts provided researchers with unique insight into the impacts of nest attentiveness on nest temperature. A distinct trend in natural bout duration was observed at both Poplar and Skimmer Islands. At both colonies, on-bouts were on average longer than

off-bouts. Regarding mean off-bout duration, those at Poplar were shorter than those at Skimmer. Skimmer off-bouts were particularly long (>7 hours) due to various daytime colonial disturbances (i.e. domestic dog and human presence) and well documented nighttime desertion caused by GHOW presence and subsequent nest depredation. These disturbances explain the observed discrepancy in the number of natural bouts observed at both colonies; in general, more were recorded on Skimmer than Poplar. On Poplar, adults left their nests frequently near dusk presumably to forage before nightfall for short intervals (<5 min) before returning to the nest. These shorter off-bouts contributed to the low average durations observed on the island. Nests 181 to 183 on Poplar were renesting attempts and perhaps due to their previous nesting failures, these adults were more prone to minor disturbances and thus deserted the nest for longer periods (Table 4C).

Overall, having missing video precludes one from determining the exact number of natural bouts that occurred across the study period. The natural bouts reported here are those where both status and duration could be verified through video review, and therefore encompass subsections of the study period. Continuous video (and iButton data for comparison below) would improve overall estimation and analysis.

Natural bout temperature trends:

Interesting natural bout temperature trends were documented on both colonies. Regardless of nest attentiveness status, average maximum bout temperature was higher across all time-of-day bins at Poplar than at Skimmer. Temperature variance, however, was greater on Skimmer. These differences in bout temperature may be due to the placement of nests

within the colonies and the surrounding vegetation or lack thereof. The majority of nests on Poplar were first created in an area of the island with minimal vegetative cover. The location of these nests left them exposed to direct sunlight, high humidity, strong winds, and heavy rainfall. The direct exposure of these nests to sunlight and the sandy nesting substrate kept nests much warmer than nests that had sufficient nearby cover. The temperature at other non-camera monitored nests reached >60ºC in some extreme cases. Egg or chick exposure at these temperatures would be fatal even after short periods. Understanding when temperatures are most harmful for incubating COTE provides researchers and managers with invaluable knowledge which may help dictate when nesting surveys should be conducted to ensure minimal nest exposure at these dangerous temperatures. Luckily, by mid- to late June, vegetation grew quickly due to fairly regular rainfall throughout the breeding season. On Skimmer, a portion of nests were situated nearby existing cover, namely American searocket (*Cakile edentula* (Bigelow) Hook), which somewhat insulated the nests from strong winds. More exposed nests contributed to the high temperature variance observed on Skimmer.

Through the incorporation of iButton temperature loggers, expected daily trends in nest temperature were observed at each colony which in turn helped illustrate when nest exposure is most detrimental to COTE at both Poplar and Skimmer. At both colonies, nest temperature was highest during the Peak bin. All nest surveying, monitoring, and equipment troubleshooting must take place outside of this time-of-day bin to avoid incurring any unnecessary stress on incubating adults. While lack of vegetative cover was

not a concern for nests at Skimmer, daily nighttime abandonment and predator disturbance contributed to the poor hatching success observed on the island.

Model predicted bouts:

The suite of a priori models used to predict bout status proved ineffective overall save for the Night bin at both Poplar and Skimmer. The best fit model was similar across all bins and colonies. The similarities in model selection across bins and colonies is most likely a product of the limited number of available covariates. While other weather-related variables were considered for inclusion within the models, the available data was insufficient or the variable was not believed to be biologically relevant to COTE and were not used during model creation. The minimal success observed in all time-of-day bins except Night may have been caused by a limited sample size of bouts since all model covariates were significant. At both colonies, the number of off-bout samples was greatest in the Night bin as was especially the case with Skimmer where off-bouts outweighed on-bouts by nearly 3:1 (Table 4H). However, on Skimmer, issues arose when predicting bout status for on-bouts due to a lack of available samples for use during model creation. This was especially evident on Skimmer where a total of only 419 on-bout samples were predicted (Table 4L).

The logistic regressions comparing whether duration or location of a predicted point within a bout affected the likelihood of being correctly predicted provided insight into how the selected models could be improved for future use. For instance, if a predicted point fell outside of the first five minutes of a bout, the likelihood of being correctly predicted

increased greatly. Similarly, the likelihood of correctly predicting bout status improved significantly with bout duration. These findings indicated that the approach used for this study is currently inadequate for identifying early stages of bouts when the nest is still transitioning from the thermal properties of the previous bout, and that these transitions take time before they are reliably identifiable.

To increase the predictive success of the models, sample size must be increased. An increase in sample size leads to an increase in statistical power of the models and thus reduces the probability of committing Type II error. It was believed that increasing sample sizes at both Poplar and Skimmer would have allowed for a more accurate classification scheme. Due to an abundance of lost iButton temperature data at both colonies, the sample sizes used to create the models were low. By ensuring proper calibration of the devices, their placement within nests, and a timely removal to prevent reaching storage capacity, the sample size of bouts could be increased. Also, increasing the number of nests being monitored with iButtons paired with video cameras is another simple solution to increase sample size. However, it must be acknowledged that the possibility of the sample size used in this study may be insufficient for the time-of-day bins except Night, or that the differences between the relevant variables are too minute to allow for accurate bout status prediction.

Managers must be careful when taking these model results into consideration. Overall, the models were better able to predict status for long bouts than short. Successfully quantifying these longer bouts is crucial to recognizing patterns of nighttime desertion and predator

disturbance at the colony. When paired with video, the cause of off-bouts as well as the status of individual bouts can be verified and this information may be utilized for future management practices. The necessity of quantifying shorter bouts is fully dependent on the management task at hand. While it is currently unknown if generally short off-bouts affect hatching success, should researchers deem any nest exposure detrimental to egg and chick health, the ability to quantify these bouts is imperative. These short exposures may be especially important to quantify at breeding colonies where extreme summer heat and humidity is commonplace. Understanding shorter bouts may also prove useful for measuring overall nest attentiveness to a higher degree of precision.

Study limitations:

Various issues arose during the course of this study regarding the iButtons. As stated previously, once the internal storage of the device was filled, the logger no longer sampled temperature. This mainly occurred when inclement weather or poor water conditions made travel to the field site unsafe late in the data collection window. To best avoid this, scheduling of field days was adjusted around weather events as much as possible but long stretches of poor field conditions still prevented consistent iButton removal across the breeding season. Precipitation events often caused tent stakes and the iButtons secured to them to sink deeper into the sand, burying the iButton underneath nesting substrate. As mentioned previously, a number of iButtons and their corresponding tent stakes could not be recovered as a result. The presence of the nest stake may have contributed to the failure of three nests on Poplar.

The nest characteristics of COTE proved to be a challenge for ensuring accurate iButton measurements. Due to the simple scrape nest structure, in an unattended nest, strong winds easily covered the iButtons which caused all subsequent data to be inaccurate and not usable. Without direct contact with the eggs, air space between eggs, or incubating adult, the iButton was unable to accurately collect temperature data from within the nest itself. Simple nest scrapes have been shown to provide little thermal differentiation from ambient conditions (Ar & Sids, 2002; Schneider & McWilliams, 2006) and the ambient temperatures may have likewise influenced nest temperatures (Ward, 1990). iButtons that stayed at the surface of the nest scrape and were not covered with sand therefore may not have gathered accurate readings from the nest. Based on the inaccuracy and lack of consistency with the temperature readings collected during this study, it is suggested that caution be taken by researchers when installing the loggers in nest to ensure deposition of nesting material onto the device does not occur. Further experimentation into developing a mechanism to prevent this is a crucial first step to future studies that wish to utilize this technology.

The video monitoring component of this study proved difficult to maintain and occasionally troubleshoot. Without expert knowledge of each system component, from solar panels to charge controllers to cameras, it was difficult to troubleshoot various power issues and some data was lost as a result. Testing and developing a solid understanding of each component pre-field season is crucial to ensuring data is collected continuously and troubleshooting in-field can be completed quickly and effectively. One major drawback to using store-bought equipment is the inability to use it with similar but different branded

equipment. For example, Lorex® cameras, the brand used in this study, (in particular the wireless models) were fully incompatible with different branded DVRs and vice versa (pers. comm. David Brinker). As of this writing, no current manufacturers of surveillance DVRs provide cross-brand capabilities for wireless cameras.

Several other considerations must be taken into account when selecting equipment for in-field use. Wired cameras must be connected directly to a DVR and they must be connected to the same power source as well. The major limitation with wired cameras is their restricted placement due to limited cable length. This may be addressed with the inclusion of extension cables, but this often decreases video quality and offers another point of potential component failure and subsequent data loss (pers. comm. David Brinker). Wireless cameras have the flexibility of increased placement options while removing the DVR-to-camera cabling. These models of cameras do, however, require their own power source and may only be placed a set distance away from the DVR without picture loss (<152 m). This may be remedied with signal extenders but these devices only work with individual cameras and may be costly (>USD $89.99 per unit).

Signal interruptions between the wireless cameras and their respective receivers were another common issue throughout this study. As mentioned in Wall et al. (2018), the wireless receivers were placed in the same box as the DVR, secured to the sides of the container with duct tape, and all were connected to the same power source. During intense heat spells, the duct tape occasionally came loose and the receivers fell to the bottom of the box. Depending on which receiver fell in relation to its respective camera's placement,

the signal for that camera was completely lost until the receiver was secured again. Even when receivers were connected and secured, occasional signal interference occurred. If a receiver did not have a completely clear line of sight to the camera, picture quality decreased and, at times, the camera was unable to correctly pair with the receiver and video was not collected. Interference was also potentially caused by nearby receivers particularly if they were aligned within the line of sight from the affected camera to the receiver.

CONCLUSION

Quantifying nest attentiveness rates and nesting behaviors of COTE is crucial to understanding how best to manage breeding colonies of this species in the future. Low nest attentiveness rates in 2017, as observed on Skimmer Island, indicate that adults were leaving nests exposed to weather and predation events for extended durations. Poplar Island, meanwhile, with higher nest attentiveness rates, was much more successful. As a result, the vast majority of nests hatched at least one chick due to adults incubating nests through the night and not exposing them for long periods during inclement weather. This high nest attentiveness also explains the normal duration of incubation periods observed across nests on Poplar. It is currently assumed that mate switching, the most frequently documented behavior, has little to no impact on nest attentiveness rates due to their short duration. Quantifying flocking behavior is more informative as duration varies greatly across colonies which may affect nest attentiveness rates differently. Reducing nesting disturbances during periods of frequent flocking will positively impact nest attentiveness rates by hopefully decreasing overall flocking duration.

This study was the first to quantify nest attentiveness rates for COTE in North America and the first to couple temperature loggers and video cameras in order to monitor breeding colonies of the species. Utilizing both technologies allowed researchers to determine the effectiveness of both monitoring techniques with a ground-nesting species. Video cameras afforded researchers with a unique opportunity to continuously monitor breeding colonies and individual nests to better calculate nest attentiveness rates and to monitor both breeding behaviors and predation events. This technology also affords researchers with an excellent, non-invasive opportunity to document behaviors at the breeding colony and monitor incubation patterns. Large gaps in video collection did exist as a result of poor power consumption calculations and lost connections between the wireless cameras and their corresponding receivers.

Throughout the breeding season, iButton temperature loggers proved to be a mostly effective technique for monitoring nest attentiveness rates. Data was unusable at some nests, however, due to inconsistent contact with the incubating adult, eggs, or nest surface. A number of loggers were buried under nesting substrate or removed entirely from the nest by incubating adults thus rendering any collected data useless. A built-in lag time within the device prevented accurate temperature readings when sampling temperature in intervals less than this value. Should researchers wish to use iButton temperature loggers in future studies involving ground-nesting species, appropriate measures to ensure constant contact with the nest surface or incubating adult must be taken.

When considering utilizing video technology in-field, ensure all equipment is tested thoroughly beforehand and all involved are able to quickly troubleshoot should any issues arise. Also, establishing clear lines of sight between camera and receiver and sufficient power throughout the entirety of the nesting season is crucial to assuring continuous video coverage is possible. In-depth knowledge of equipment is especially important when monitoring endangered or threatened species with little tolerance to disturbance. Placing DVRs, power supplies, and any non-essential in-colony equipment well outside the breeding colony further ensures minimal disturbance and ease of troubleshooting.

For researchers considering utilizing iButtons for future studies, proper calibration and in-nest installation of the device is vital. Proper calibration assures that internal data storage does not fill prematurely and data is lost before researchers access the colony again. Determining a sampling interval that best suits the frequency with which the colony will be surveyed will prevent this from occurring. As stated previously, improper installation of the iButton and its associated staking system may cause it to sink into the nesting substrate rendering all subsequent data useless. Training all involved in proper installation pre-field season will allow loggers to be installed in a streamlined fashion and minimize total researcher disturbance. If the composition of the nesting substrate within the breeding colony is well understood before installation, nests situated in ideal locations can be selected for monitoring purposes and the installation issues observed occasionally at Poplar may be avoided entirely.

5. RECRUITMENT STRESSORS, ISLAND LOSS, AND NEST ATTENTIVENESS RATES OF COMMON TERNS (*Sterna hirundo*): A REVIEW

The common tern (*Sterna hirundo*) (hereafter COTE) is a waterbird species of great concern in the state of Maryland. Recently listed as endangered in August of 2016, the species has experienced a steady decline in the number of breeding pairs and breeding colonies since the 1980s (Erwin et al., 2011). The future of the species in Maryland is uncertain as the effects of climate change continue. Researchers predict that sea levels will continue to rise, thus eroding the remaining breeding colony habitat, and that water temperatures will increase, creating larger and more powerful storm events which will worsen rates of erosion (Zervas, 2001; Naijar et al, 2010). Loss of island habitat has caused COTE to nest closer to shore where mammalian predators may easily enter the breeding colony and depredate chicks and eggs (Erwin et al., 2003; Erwin et al., 2011). Presence of these predators forces COTE to nest in suboptimal habitat which may be at a greater influence of sea level rise, erosion, and powerful weather events (Nisbet et al., 2017).

Nest attentiveness, or time in which at least one nesting adult is present at the nest, is a key indicator of breeding colony health. This rate may be influenced by predator presence, food availability, or high temperatures (Martin, 1987; Nisbet et al., 2017). Predators negatively affect nest attentiveness by causing nesting adults to temporarily abandon the nest when they enter the colony. Low food availability forces incubating adults to forage further away from the nest, thus leaving it unattended and exposed for a longer duration. High temperatures cause nesting adults to leave the nest in order to drink water more frequently and soak their bodies to cool the nest, eggs, and chicks. Even short exposure to high

temperatures may lead to improper embryo development and chick death (Nisbet et al., 2017).

Currently, there are 14 waterbird species that breed in the state of Maryland. All of these species have experienced declines in breeding pair numbers since the 1880s as a result of anthropogenic activities such as the millinery trade, urban shoreline development, and habitat destruction (Brinker et al., 2007). As such, waterbird breeding population trends have been monitored in Maryland since the 1980s (Erwin et al., 2003; Brinker et al., 2007; Erwin et al., 2011). A more recent study (Erwin et al., 2011) identified 200 potential nesting islands for waterbird species in the Chesapeake Bay. Of a subset of 17 of these islands located within the Tangier Sound, 15 had experienced habitat loss due to erosion since 1977. Over this same time period, waterbird breeding population numbers reflected this trend and declined by over 60% (Erwin et al., 2011).

Through a comprehensive analysis of Landsat imagery obtained from 1986, 1991, 1996, 2006, 2011, and 2016, island loss was documented in both the Chesapeake Bay and the Delmarva coastal bays of Maryland and Virginia. A total of 536 habitat islands, composed partially or entirely of wetland and beach, were documented during this analysis; the majority (70.9%) of which were located in the Delmarva coastal bays. A subset of 140 islands detected in imagery from five or more years was used to document trends in habitat area over time. All land covers (wetland, beach, agriculture/open field, forest, and urban) experienced a decline in area between 1986 and 2016. A total of 1,213.69 hectares (ha) of area were lost over this thirty-year period.

Both wetland and beach habitat experienced intriguing trends over the study period. Wetland habitat increased by 17% from 1986 to 2006 before declining by 16.11% between 2006 and 2011. A possible explanation for this trend is the impact of both Tropical Storm Hanna and Hurricane Irene on the region. It was surmised that, due to these storms, tidal inundation, perimeter erosion, and degradation of wetlands may have led to the observed decline in wetland habitat. Beach habitat experienced the most interesting trend among all land covers. Two distinct peaks in beach habitat occurred between 1986 and 2016 with sharp increases in area occurring between 1991 and 1996 (20% increase) and 2006 and 2011 (11% increase). These increases can be attributed to large accretions of sand on the Delmarva coastal islands in Virginia and the construction of Poplar Island. This study was the first to document the impact of Poplar Island's construction on available beach habitat in the region.

To determine changes in breeding colony area and breeding population numbers, centroids of island polygons created during the aforementioned image analysis were displayed within a GIS program (ArcMap 10.4) and Google Earth over historical Landsat satellite imagery. Areas of each colony polygon were documented from 1986 to 2016 based on analyzed Landsat imagery from 1986, 1991, 1996, 2006, 2011, and 2016. COTE breeding population numbers collected during annual breeding surveys were obtained from an extensive database provided by David Brinker of the Maryland Department of Natural Resources Natural Heritage Program. All population trends were documented across the years

mentioned above. 1996 data, however, was not included in any analyses due to low sampling effort.

Both breeding colony numbers and breeding population declined between 1986 and 2016. A total of 62 COTE breeding colonies were observed between 1985 and 2017. The lowest number of active breeding colonies (2) occurred in 2017 and the lowest number of surveyed breeding pairs was 349 in 2011. An overall decline of 80% in breeding pair numbers was observed between 1986 and 2016. Surveyed breeding colonies also declined during this period (-64.71%). An average of 1.8 breeding colonies was lost every 5 years with a total of 11 colonies (18.33%) lost from erosion over the thirty-year period.

Beach habitat area at the breeding colonies surprisingly increased between 1986 and 2016 by 1.78%. Declines were observed between 1986 and 1991 (-5.05%) and 1996 and 2006 (-13.74%), before increasing between 2006 and 2011 due to the aforementioned construction of Poplar Island. Construction began in the late 1990s, directly in between 1996 and 2006; therefore, the increase in area was not documented until 2006. Area increased slightly between 2006 and 2011 (11.07%) but declined again between 2011 and 2016 (-6.61%). The observed increase in area between 2006 and 2011 was attributed to the large deposition of sandy material on Poplar Island in 2011.

Through the construction of a surveillance system composed of video cameras and temperature loggers placed in-nest, nest attentiveness rates for COTE were characterized in both the Chesapeake Bay (Poplar Island) and Delmarva coastal bays of Maryland

(Skimmer Island). These two islands were the only active breeding colony sites for COTE in 2017. Six video cameras (five nest and one elevated colony camera) were placed on Poplar and Skimmer Islands. A subset of nests had iButton temperature loggers placed in them (37 on Poplar and 39 on Skimmer); each camera nest also had a logger. Video was collected continuously and nest temperature was collected in 3 min sampling intervals. Four time-of-day bins (Morning, Peak, Cooling, and Night) were created to determine if any trends in nest temperature occurred throughout a 24-hour period. Bout duration, or consecutive periods of time in which the nest was occupied or not, was calculated within R and bout status (either "on" or "off") was predicted for iButton data using a suite of a priori models. These bouts were subsequently placed into the aforementioned time-of-day bins. A logistic regression was also calculated to determine the effect of bout duration and location within a bout on the model's predictive success. For every video monitored nest, nesting behavior and predation events were documented. Data from both the DVRs and iButtons were collected during nesting surveys biweekly from Poplar Island and once weekly from Skimmer Island.

A total of 76 nests were monitored with iButtons (37 on Poplar and 39 on Skimmer) during the 2017 field season. The approximate deployment duration for both Poplar and Skimmer iButtons was 25 d. A total of four iButtons on Poplar and five on Skimmer could not be recovered due to nest wash-out, removal of the logger by an incubating adult, or another unknown reason. On Poplar, approximately 9 d of data were lost whereas Skimmer fared much better with only 2 d of lost data. Data was primarily lost due to the logger not being calibrated properly before use or incorrect placement of the logger within the nest. Poor

placement of the iButton occasionally lead to burial of the device underneath nesting substrate which rendered all subsequently collected data highly inaccurate and unusable.

A total of 13 nests were monitored with video cameras in 2017 (8 on Poplar and 5 on Skimmer). Three of the 13 nests failed within three days of camera deployment on Poplar. A total of 3,802.48 h of video were collected in 2017. Of this video, 2,037.26 h were useable for review. Over 5,000 h of video were lost primarily from incorrect power consumption calculations. Cameras were deployed on Poplar for an average of approximately 14.4 d whereas all Skimmer cameras were deployed for 54 d.

Video reviewers documented 714 behavior events across both colonies. Mate switching, in which the incubating adult switches with their mate, comprised the majority (67.65%, n = 483) of behavior events with flocking, when the majority or a portion of the breeding colony abandon their nests temporarily, being the second most documented behavior (19.19%, n = 137). Colonies with high frequency of flocking behavior have lower rates of nest attentiveness and tend to experience lower overall nesting success. Mate switching, which often lasted less than one minute, has not been shown to impact nest attentiveness rates. Therefore, documentation of this behavior was not considered an effective indicator of a decline in colonial nest attentiveness rates. Mating was never documented at the colony as cameras were placed at the nest site after clutch completion occurred and mating ceased for the season.

The count, duration, and nest temperature trends of natural bouts varied by nest and by colony. Average on-bout duration on Poplar ranged from 35 to 213 min whereas Skimmer on-bouts ranged from 53 to 188 min. On average, off-bout duration was lower on Poplar (4 to 26 min) than Skimmer (29 to 40 min). Of Poplar on-bouts, the highest average minimum temperature occurred during the Cooling bin (35.56ºC) while the lowest occurred during the Morning bin (31.17ºC). Off-bout minimum temperature on Poplar was highest during the Peak bin (36.12ºC) and lowest during the Night bin (31.16ºC). For both on- and off-bouts on Skimmer, the highest average minimum temperature was recorded during the Peak bin (31.98ºC (on-bout); 34.43ºC (off-bout)) while the lowest was recorded during the Night bin (23.65ºC (on-bout); 21.94ºC (off-bout)). Maximum on- and off-bout temperature was highest during the Peak bin at both colonies (36.24ºC (Poplar on-bout); 36.22ºC (Poplar off-bout); 34.95ºC (Skimmer on-bout); 34.88ºC (Skimmer off-bout)). For both Poplar and Skimmer, off-bout temperature was warmer on average than on-bout temperature for all bins except the Night bin. On-bout temperature was greater during this time-of-day bin due to the insulating properties of incubating adults.

A total of six models were created to predict bout status for iButton bouts. The most complex model was the best fit for predictive purposes at nearly all time-of-day bins except one (Poplar Morning bin). At both colonies, the models were only effective at predicting bout status when a bout occurred during the Night bin. In all other time-of day bins, models predicted every bout status as on. Off-bouts were not well recognized by this modeling approach with only a 25% success rate at Poplar and 50% success rate at Skimmer. The predictive success of the Night bin model was greater on Poplar (81.58%) than Skimmer

(78.39%). The models were also more successful at predicting longer bouts (69.79% and 81.32% success rate of predicting bout status for bouts longer than 60 min in duration). Regarding bout duration's impact on model predictive success on Poplar, the likelihood of correctly predicting attentiveness status ranged from 1.0004 (Night) to 1.091 (Morning) ($p < 0.001$ for all time-of-day bins) times as likely for each one-minute increase in bout duration. Predicted points during Poplar bouts which occurred after the first five minutes of a bout ranged from 1.394 ($p = 0.015$; Morning bin) to 3.979 ($p < 0.001$; Night bin) times as likely to be correctly predicted. Much like Poplar, the likelihood of correctly predicting bout status on Skimmer ranged from 1.0004 ($p < 0.001$; Night bin) to 1.091 ($p < 0.001$; Morning bin). For predicted points outside the first five minutes of a bout, the likelihood of being accurately predicted was much higher for Skimmer than Poplar and ranged from 6.682 (Cooling) to 11.846 (Peak) times as likely to be correctly predicted.

Multiple threats continue to impact COTE populations today. Despite construction of Poplar Island, total island habitat loss has worsened due to sea level rise and subsequent erosion. Mirroring this habitat loss, breeding pair numbers have declined precipitously since 1986. Total area of beach habitat at historic breeding colonies did increase between 1986 and 2016 but other disturbances, such as predator presence, negatively impacted the breeding population of COTE in Maryland. Nearly a dozen former COTE breeding colonies were lost completely due to erosion over the same time period. This loss of breeding habitat forced breeding COTE to nest in suboptimal habitat near the shoreline which may have exposed the species to predation and other colonial disturbances (as was the case on Skimmer Island).

Nest attentiveness rates were greatly affected by nesting disturbances. On Skimmer Island, most natural off-bouts were initiated during the Cooling bin (1600-2000) whereas on Poplar, most natural off-bouts were initiated during the Morning bin (0500-1200). The duration of natural off-bouts at Skimmer Island was, on average, long enough to negatively affect nest attentiveness rates. Off-bout duration was particularly long at this breeding colony due to the aforementioned predator presence and other colony-wide disturbances. These extended periods of nest abandonment exposed the nests to various predators and adverse weather events. Video off-bouts further corroborated this observation: Skimmer nests experienced longer and more frequent off-bouts than Poplar nests. As one would expect, this increase in frequency and duration of off-bouts negatively affected overall nesting success. Skimmer Island experienced high rates of nest predation which caused adults to abandon the nest for extended periods of time and decreased overall nest attentiveness and nesting success.

RECOMMENDATIONS

This study successfully documented island loss in the Chesapeake Bay and Delmarva coastal bays across a thirty-year period from 1986 to 2016 and it was the first to document this loss beyond the mid-2000s. This study was also the first to document the impact the construction of Poplar Island has had on available island habitat in the region. While Poplar Island had initially had a great impact on the amount of habitat available, habitat area has continued to decline since 2011 due to sea level rise and increased rates of erosion. Managing what island habitat is currently available is essential for preserving the future of

COTE in Maryland. Construction of berms or riprap would reduce the impact of erosion on islands by deflecting wave energy away from the island's perimeter. The supplementation of material (both in the form of sand and dredged material) on existing islands has shown great promise for COTE breeding populations in Maryland. While less cost effective, the construction of entirely new islands would provide the most benefit for COTE. These islands would afford this species optimal nesting habitat that is removed from predators and sufficiently elevated to reduce the impacts of sea level rise.

To preserve breeding populations of COTE in Maryland, it is imperative to continue conserving island habitat through supplementation of material and predator removal. Currently, only two islands in the Chesapeake Bay and one in the Isle of Wight Bay are actively receiving material supplementation. Other potential supplementation sites (Barren and James Islands in Maryland) are in close proximity to the mainland which may promote mammalian colonization and dissuade COTE from nesting there as a result (Erwin et al., 2011). Tangier Sound, a portion of the Chesapeake Bay used previously by breeding COTE, may be the ideal setting for the creation of several small manmade islands as existing, previously utilized islands are removed from the mainland and do not have populations of known mammalian predators of nesting COTE (Erwin et al., 2011). However, shifts in public policy since the 1980s regarding the use of dredged material for habitat creation may halt the construction of new islands for nesting waterbird use (Erwin et al., 2003). Future sites for material deposition typically are diked, have tall steep sides, and are overpopulated with the native grass species *Phragmites australis*. This species colonizes open space prolifically thus driving COTE to nest in suboptimal habitat

elsewhere (Soots & Landin, 1978). Another shift in public policy may be required before further construction of new islands for breeding COTE usage.

Understanding nest attentiveness rates of incubating adults is crucial to better preserving breeding populations of endangered waterbird species. This study was the first to couple video cameras with temperature loggers in order to assess this for breeding COTE. iButtons proved to be an overall effective technique at monitoring nest attentiveness however, the loggers occasionally failed to accurately monitor nest temperature due to burial under nesting substrate; even a minute amount of substrate on the surface of the logger could render data useless. Should researchers choose to utilize this technology in the future, construction of an apparatus to ensure direct contact with the incubating adult or airspace within the nest is paramount. Video cameras, however, were a highly accurate and effective means of documenting both nest attentiveness rates and breeding behaviors of COTE. To ensure continuous data coverage throughout the breeding season, accurate power consumption calculations must be conducted. The addition of extra power sources, in the form of batteries or solar panels, would ensure this.

Future monitoring of COTE breeding colonies in Maryland would benefit from the incorporation of video technology. If predation has not been documented but is suspected, this technology would provide continuous monitoring of the colony and may provide further insight. For sensitive nesting species like COTE, video technology provides a minimally invasive but effective means of monitoring breeding colonies. Individual system components are often cost-effective (<USD $100 to >USD $300/unit) and provide a wide

range of resolution, lighting, and weatherproofing options. Should researchers wish to utilize this technology for future in-colony monitoring, all non-essential in-colony components (power sources, DVRs, etc.) should be placed outside the perimeter of the colony to ensure minimal researcher disturbance and for ease of access for troubleshooting purposes.

Several unknowns still exist today regarding the ecology of the Chesapeake Bay and its impact on the breeding populations of COTE in the region (Erwin et al., 2011). Commercial fisheries, one of the primary economic drivers in the region, may have had lasting impacts on the species for decades through overharvesting and associated ecological effects. A comprehensive assessment of both prey and non-prey fish populations in the region is warranted to address this knowledge gap. Runoff into the Chesapeake Bay containing newly created chemicals and pesticides may also be negatively affecting the species through alterations in water quality and subsequent impacts to fish populations (Erwin et al., 2011). In order to develop more effective management recommendations for COTE in the future, these data gaps must be addressed and fully understood.

TABLES

Table 2A: Spectral details of the Landsat 4-5 Thematic Mapper (TM) satellites. Note that band 6 data was acquired in 120 m resolution but USGS products were resampled to 30 m pixels.

Band Number	Band Description	Wavelength (μm)	Resolution (m)
1	Blue	0.45-0.52	30
2	Green	0.52-0.60	30
3	Red	0.63-0.69	30
4	Near Infrared (NIR)	0.76-0.90	30
5	Shortwave Infrared (SWIR) 1	1.55-1.75	30
6	Thermal	10.40-12.50	120
7	Shortwave Infrared (SWIR) 2	2.08-2.35	30

Table 2B: Spectral details of the Landsat 8 Operational Land Imager (OLS) and Thermal Infrared Sensor (TIRS) satellite. Note that data from bands 10 and 11 (TIRS sensors) was acquired in 100 m resolution but USGS products were resampled to 30 m pixels.

Band Number	Band Description	Wavelength (μm)	Resolution (m)
1	Ultra Blue (coastal/aerosol)	0.435-0.451	30
2	Blue	0.452-0.512	30
3	Green	0.533-0.590	30
4	Red	0.636-0.673	30
5	Near Infrared (NIR)	0.851-0.879	30
6	Shortwave Infrared (SWIR) 1	1.566-1.651	120
7	Shortwave Infrared (SWIR) 2	2.107-2.294	30
8	Panchromatic	0.503-0.676	15
9	Cirrus	1.363-1.384	30
10	Thermal Infrared (TIRS) 1	10.60-11.19	100
11	Thermal Infrared (TIRS) 2	11.50-12.51	100

Table 2C: Python island selection accuracy for Worldwide Reference System (WRS) path 14, row 33. A Python script was created to automate the island selection process after the land/water raster mask was created. The accuracy for this scene was particularly low due to the segmentation process blending small islands in with the surrounding shoreline or nearby water pixels thus essentially deleting them from view.

Year	Selected Islands	Total Islands	Percent Selected	Percent Missed
1986	25	102	0.245	0.755
1991	30		0.294	0.706
1996	43		0.422	0.578
2006	28		0.275	0.725
2011	30		0.294	0.706
2016	32		0.314	0.686

Table 2D: Python island selection accuracy for Worldwide Reference System (WRS) path 14, row 34 in the Chesapeake Bay. A Python script was created to automate the island selection process after the land/water raster mask was created. The accuracy varied between the Chesapeake Bay and Delmarva coastal islands greatly primarily due to the large number of wetland islands that were erased or blended into the shoreline after the segmentation process. As such, whole scene island selection accuracy was divided into the two regions. Other islands throughout the scene were simply missed by the computer and not detected.

Year	Selected Islands	Total Islands	Percent Selected	Percent Missed
1986	51	117	0.436	0.564
1991	48		0.410	0.590
1996	70		0.598	0.402
2006	50		0.427	0.573
2011	46		0.393	0.607
2016	45		0.385	0.615

Table 2E: Python island selection accuracy for Worldwide Reference System (WRS) path 14, row 34 in the Delmarva coastal bays. A Python script was created to automate the island selection process after the land/water raster mask was created. The accuracy varied between the Chesapeake Bay and Delmarva coastal islands greatly primarily due to the large number of wetland islands that were erased or blended into the shoreline after the segmentation process. As such, whole scene island selection accuracy was divided into the two regions. Other islands were simply missed by the computer and not detected.

Year	Selected Islands	Total Islands	Percent Selected	Percent Missed
1986	53	278	0.191	0.809
1991	59		0.212	0.788
1996	86		0.309	0.691
2006	67		0.241	0.759
2011	116		0.417	0.583
2016	87		0.313	0.687

Table 2F: Python island selection accuracy for Worldwide Reference System (WRS) path 15, row 33. A Python script was created to automate the island selection process after the land/water raster mask was created. The accuracy of this scene was particularly high due to the number of large conspicuous islands and small number of total islands present.

Year	Selected Islands	Total Islands	Percent Selected	Percent Missed
1986	35	39	0.897	0.103
1991	34		0.872	0.128
1996	30		0.769	0.231
2006	30		0.769	0.231
2011	27		0.692	0.308
2016	31		0.795	0.205

Table 2G: Cohen's Kappa values to assess land cover classification accuracy assessment of Landsat 4-5 TM and 8 OLS/TIRS scenes along Worldwide Reference System (WRS) paths 14 and 15, rows 33 and 34. Kappa values range from 0 to 1 (i.e. complete disagreement to complete agreement between groundtruthed and classified land covers). WRS path 14, row 33 Kappa values are significantly low due to the artifact of using Landsat imagery for digitizing small, highly complex islands.

Year	Path 14, Row 33	Path 14, Row 34	Path 15, Row 33
1986	0.551	0.764	0.678
1991	0.236	0.695	0.815
1996	0.181	0.735	0.694
2006	0.093	0.680	0.633
2011	0.237	0.666	0.604
2016	0.231	0.559	0.662

Table 3A: Number of total nesting colony sites as determined through GIS analyses, total number of groundtruthed islands within Google Earth imagery, and the total number of nesting colony sites correctly detected from 1986 to 2016. Note that 1996 data is not included due to incomplete surveying efforts. Total nesting colony sites are a count of all historic and current nesting colony sites in Maryland. See Methods for a description of island polygons. Percent detected remained quite low across the survey period due to low initial detection rates during image processing (see Methods).

	1986	1991	2006	2011	2016
Total nesting colony sites	58	57	44	44	40
Total groundtruthed sites	57	57	55	49	48
Total nesting colony sites detected (%)	20 (35.09%)	26 (45.61%)	18 (32.73%)	21 (42.86%)	17 (35.42%)

Table 3B: Breeding colony island area (ha) in Maryland from 1986 to 2016. Note that 1996 data is not included due to incomplete surveying efforts. Total colony area includes all islands no matter their detection rate. Subset area is a summation of area from 11 colonies detected in 5+ imagery years. A sharp increase between 1996 and 2006 was detected in both methods due to the construction of Poplar Island in the late 1990s (see Discussion).

	1986	**1991**	**2006**	**2011**	**2016**
Total colony area	131.36	1253.35	442.29	376.75	506.87
Average total colony area (±SD)	7.72 ± 11.99	5.45 ± 10.90	27.64 ± 92.10	19.83 ± 72.49	29.82 ± 111.68
Subset area	109.76	99.99	435.60	361.58	501.16
Average subset area (±SD)	9.98 ± 14.62	8.33 ± 13.68	39.60 ± 110.55	30.13 ± 91	41.76 ± 132.71

Table 4A: Time-of-day bin start and end times. Details regarding the creation of the bins can be found in the Methods section.

Bin	**Start Time**	**End Time**
Morning	5:30	12:00
Peak	12:00	16:00
Cooling	16:00	20:00
Night	20:00	5:30

Table 4B: Time-of-day bin definitions. These definitions are based on the average values of cumulative off-bout degree difference and total off-bout duration. The temperature and time values displayed here are the minimal values required for designation of a footage off-bout within said bin.

Bin	**Definition**
Morning	+0.5°C over 30 minutes
Peak	+0.5°C over 60 minutes
Cooling	-1.5°C over 60 minutes
Night	-2.0°C over 120 minutes

Table 4C: Count and average duration of natural bouts by status and nest for Poplar Island, MD. The number of both on- and off-bouts were nearly identical while average duration varied greatly. Across all nests, on-bouts were longer than off-bouts.

Nest Number	Number of Off-Bouts	Number of On-Bouts	Average Off-Bout duration (min)	Average On-Bout Duration (min)
2	79	74	12	35
21	36	30	4	213
24	62	57	4	142
64	34	32	5	96
71	55	51	26	120
181	231	235	20	35
182	91	94	23	57
183	148	146	14	56

Table 4D: Count and average duration of natural bouts by status and nest for Skimmer Island, MD. The number of both on- and off-bouts were nearly identical for Nests 52 and 60 while average duration varied greatly. For Nests 19, 44, and 67, more off-bouts were recorded than on-bouts. Overall, on-bouts were longer than off-bouts for all nests. Off-bouts at Skimmer Island were much longer at Poplar Island due to daily nighttime desertion.

Nest Number	Number of Off-Bouts	Number of On-Bouts	Average Off-Bout duration (min)	Average On-Bout Duration (min)
19	132	116	33	59
44	61	52	39	188
52	119	115	40	100
60	349	348	29	71
67	303	294	31	53

Table 4E: Minimum, maximum, average, and variance of bout temperature by bout status and time-of-day bin for Poplar Island, MD.

		Min T			Max T			Average T			Variance	
Bin	**Bout Status**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**
Morning	On	147	31.17	0.12	147	32.57	0.11	147	31.86	0.11	147	0.49
	Off	28	32.69	0.19	28	32.84	0.17	28	32.76	0.18	28	0.03
Peak	On	109	35.07	0.12	109	36.24	0.1	109	35.66	0.11	109	0.27
	Off	16	36.12	0.22	16	36.22	0.19	16	36.17	0.2	16	0.02
Cooling	On	16	35.56	0.19	16	35.19	0.17	16	34.89	0.18	16	0.07
	Off	13	35	0.19	13	35.15	0.17	13	35.09	0.18	13	0.02
Night	On	23	31.22	0.19	23	31.91	0.17	23	31.56	0.18	23	0.08
	Off	19	31.16	0.19	19	31.97	0.17	19	31.51	0.18	19	0.18

Table 4F: Minimum, maximum, average, and variance of bout temperature by bout status and time-of-day bin for Skimmer Island, MD.

		Min T			Max T			Average T			Variance	
Bin	**Bout Status**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**	**SE**	**n**	**$\bar{x}$**
Morning	On	104	25.86	0.18	104	29.16	0.17	104	27.42	0.16	104	1.93
	Off	80	27.45	0.19	80	27.81	0.17	80	27.63	0.16	80	0.13
Peak	On	96	31.98	0.18	96	34.95	0.16	96	33.39	0.16	96	4.57
	Off	71	34.43	0.18	71	34.88	0.16	71	34.65	0.16	71	1.4
Cooling	On	355	31.23	0.18	355	31.92	0.17	355	31.56	0.16	355	0.14
	Off	333	31.48	0.19	333	31.7	0.18	333	31.59	0.17	333	0.05
Night	On	96	23.65	0.18	96	25.2	0.16	96	24.29	0.16	96	0.65
	Off	78	21.94	0.18	78	25.96	0.17	78	23.16	0.16	78	2.58

Table 4G: Sample dataset from Poplar Island, MD used to create a priori models for predicting bout status. The success of the Night bin models can be attributed to the much larger sample size of off-bouts as compared to those of other time-of-day bins.

Bin	**Status**	
	On	**Off**
Morning	10778	782
Peak	7650	559
Cooling	7931	946
Night	11879	5357

Table 4H: Sample dataset from Skimmer Island, MD used to create a priori models for predicting bout status. The success of the Night bin models can be attributed to the much larger sample size of off-bouts as compared to those of other time-of-day bins.

Bin	**Status**	
	On	**Off**
Morning	12382	809
Peak	7932	438
Cooling	9032	1629
Night	5455	18358

Table 4I: Model selection table for predicting bout status on Poplar Island, MD. All time-of-day bins except Morning used the most complex model (model number 6) to predict bout status.

Time-of-Day Bin	Model #	Model	AIC	ΔAIC	Model Weight	k	n
Morning	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	5478.6		0.731	3	11560
	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	5480.6	2	0.269	4	11560
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	5549.6	71	0	3	11560
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	5561.1	82.5	0	2	11560
	2	BoutStatus_logistic~RectifiedTemp	5562.3	83.7	0	1	11560
	1	BoutStatus_logistic~1	5724.4	245.8	0	1	11560
Peak	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	3768.9		1	4	8200
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	3817.7	48.8	0	3	8200
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	3839.1	70.2	0	3	8200
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	3947	178.1	0	2	8200
	2	BoutStatus_logistic~RectifiedTemp	3977.7	208.8	0	1	8200
	1	BoutStatus_logistic~1	4083.7	314.8	0	1	8200
Cooling	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	5459.1		1	4	8319
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	5484	24.9	0	3	8319
	2	BoutStatus_logistic~RectifiedTemp	5590.7	131.6	0	1	8319
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	5592.3	133.2	0	2	8319
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	5594.1	135	0	3	8319
	1	BoutStatus_logistic~1	5879	419.9	0	1	8319
Night	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	14254		1	4	17006
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	14333	79	0	3	17006
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	14904	650	0	3	17006
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	15117	863	0	2	17006
	2	BoutStatus_logistic~RectifiedTemp	21162	6908	0	1	17006
	1	BoutStatus_logistic~1	21193	6939	0	1	17006

Table 4J: Model selection table for predicting bout status on Skimmer Island, MD. All time-of-day bins used the most complex model (model number 6) to predict bout status.

Time-of-Day Bin	Model #	Model	AIC	ΔAIC	model weight	k	n
Morning	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	5897.4		1	4	13191
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	5950.8	53.4	0	3	13191
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	6013.6	116.2	0	3	13191
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	6051.8	154.4	0	2	13191
	2	BoutStatus_logistic~RectifiedTemp	6084.2	186.8	0	1	13191
	1	BoutStatus_logistic~1	6086	188.6	0	1	13191
Peak	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	3202.5		1	4	8524
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	3268.6	66.1	0	3	8524
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	3289.9	87.4	0	3	8524
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	3336.4	133.9	0	2	8524
	2	BoutStatus_logistic~RectifiedTemp	3455.2	252.7	0	1	8524
	1	BoutStatus_logistic~1	3467.1	264.6	0	1	8524
Cooling	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	8807.4		1	4	10681
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	8886.2	78.8	0	3	10681
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	8949.8	142.4	0	3	10681
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	8988.4	181	0	2	10681
	2	BoutStatus_logistic~RectifiedTemp	8995.1	187.7	0	1	10681
	1	BoutStatus_logistic~1	9121.1	313.7	0	1	10681
Night	6	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure+RectifiedTemp:AmbientTemp	25001		1	4	24515
	5	BoutStatus_logistic~RectifiedTemp+AmbientTemp+RectifiedTemp:AmbientTemp	25140	139	0	3	24515
	4	BoutStatus_logistic~RectifiedTemp+AmbientTemp+AmbientPressure	25783	782	0	3	24515
	3	BoutStatus_logistic~RectifiedTemp+AmbientTemp	25798	797	0	2	24515
	2	BoutStatus_logistic~RectifiedTemp	25954	953	0	1	24515
	1	BoutStatus_logistic~1	26410	1409	0	1	24515

Table 4K: Predictive success by duration and time-of-day bins for Poplar Island, MD. In general, as bout duration increased, the likelihood of the bout being correctly predicted increased. For the Night bin, the only time-of-day bin with any true predictive success, the percentage of correctly selected bout statuses decreased as duration increased except for bouts longer than 60 min in duration.

Time-of-Day Bin	Duration Bin	True On	False On	True Off	False Off	Correct On (%)	Correct Off (%)	Correct Cumulative (%)
Morning	<4	32	160	0	0	16.67	0	16.67
	4-9	101	131	0	0	43.54	0	43.54
	10-29	505	256	0	0	66.36	0	66.36
	30-59	692	24	0	0	96.95	0	96.95
	60+	6768	1	0	0	99.99	0	99.99
Peak	<4	9	124	0	0	6.77	0	6.77
	4-9	31	27	0	0	53.45	0	53.45
	10-29	333	90	0	0	78.72	0	78.72
	30-59	636	80	0	0	88.83	0	88.83
	60+	4743	77	0	0	98.40	0	98.40
Cooling	<4	12	99	3	0	10.81	100	13.16
	4-9	109	132	0	2	45.23	0	44.86
	10-29	440	142	0	6	75.60	0	74.83
	30-59	414	62	0	0	86.95	0	86.95
	60+	4562	252	0	4	94.77	0	94.69
Night	<4	3	56	9	0	5.09	100	17.65
	4-9	27	74	20	12	26.73	62.50	35.34
	10-29	166	66	43	79	71.55	35.25	59.04
	30-59	184	112	18	92	62.16	16.36	49.75
	60+	6826	508	3119	1350	93.06	69.79	84.25

Table 4L: Predictive success by duration and time-of-day bins for Skimmer Island, MD. In general, as bout duration increased, the likelihood of the bout being correctly predicted increased. For the Night bin, the only time-of-day bin with any true predictive success, the percentage of correctly selected bout statuses decreased as duration increased except for bouts longer than 60 min in duration.

Time-of-Day Bin	Duration Bin	True On	False On	True Off	False Off	Correct On (%)	Correct Off (%)	Correct Cumulative (%)
Morning	<4	9	117	0	0	7.14	0	7.14
	4-9	38	19	0	0	66.67	0	66.67
	10-29	159	90	0	0	63.86	0	63.86
	30-59	439	83	0	0	84.09	0	84.09
	60+	8642	297	0	0	96.68	0	96.68
Peak	<4	10	88	0	0	10.20	0	10.20
	4-9	59	42	0	0	58.42	0	58.42
	10-29	135	56	0	0	70.68	0	70.68
	30-59	209	42	0	0	83.27	0	83.27
	60+	5645	107	0	0	98.14	0	98.14
Cooling	<4	83	332	2	1	20	66.67	20.34
	4-9	360	357	0	0	50.21	0	50.21
	10-29	1002	199	0	0	83.43	0	83.43
	30-59	1310	99	0	0	92.97	0	92.97
	60+	4004	260	0	1	93.9	0	93.88
Night	<4	3	12	34	15	20	69.39	57.81
	4-9	16	6	22	39	72.73	36.07	45.78
	10-29	33	0	10	203	100	4.69	17.48
	30-59	54	0	0	338	100	0	13.78
	60+	313	162	13927	3199	65.89	81.32	80.91

FIGURES

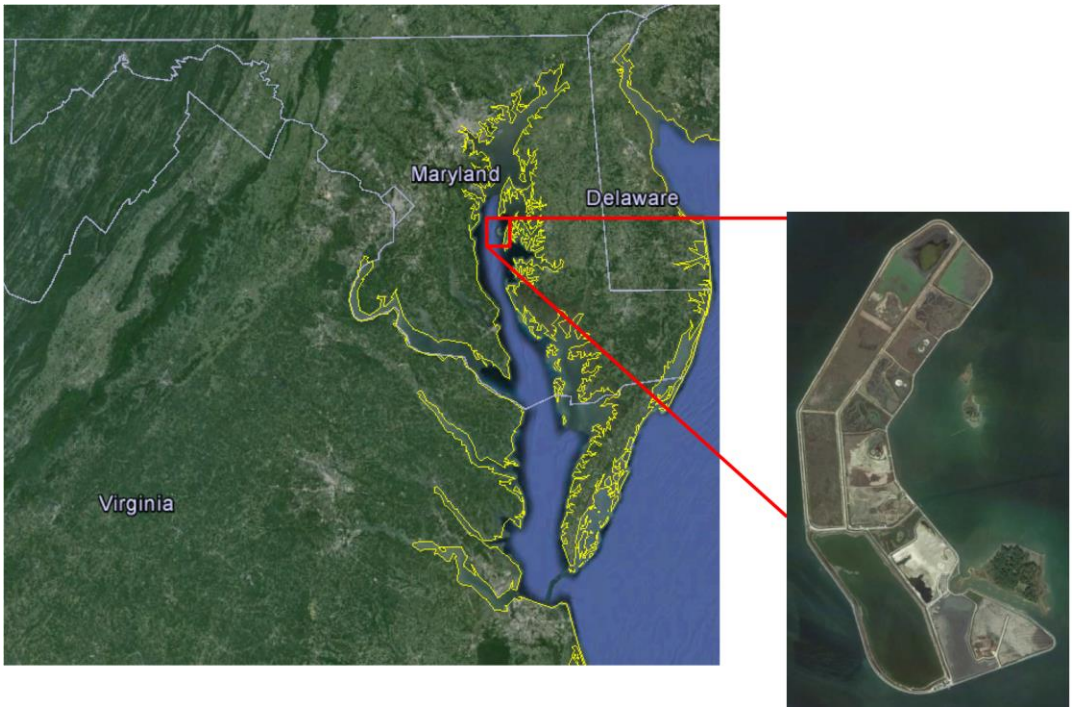

Figure 1A: Map of the Chesapeake Bay and surrounding states highlighting location of Poplar Island, MD. Imagery from Google Earth, 2016.

Figure 1B: Map of the Chesapeake Bay and surrounding states highlighting location Ocean City, MD and Skimmer Island in the Isle of Wight. Imagery from Google Earth, 2016.

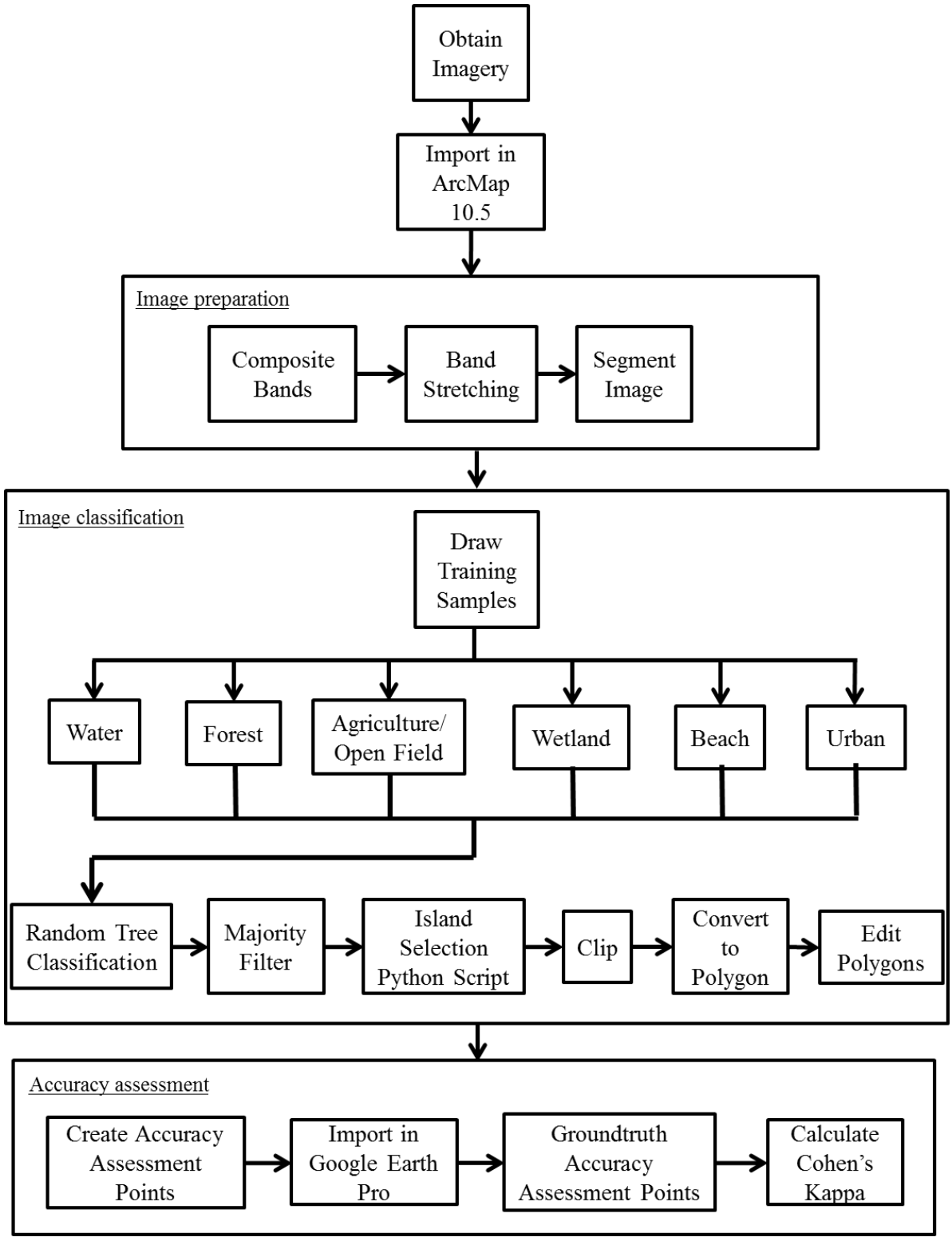

Figure 2A: Flow chart illustrating each step in the image analysis process. For details about individual steps, see Methods.

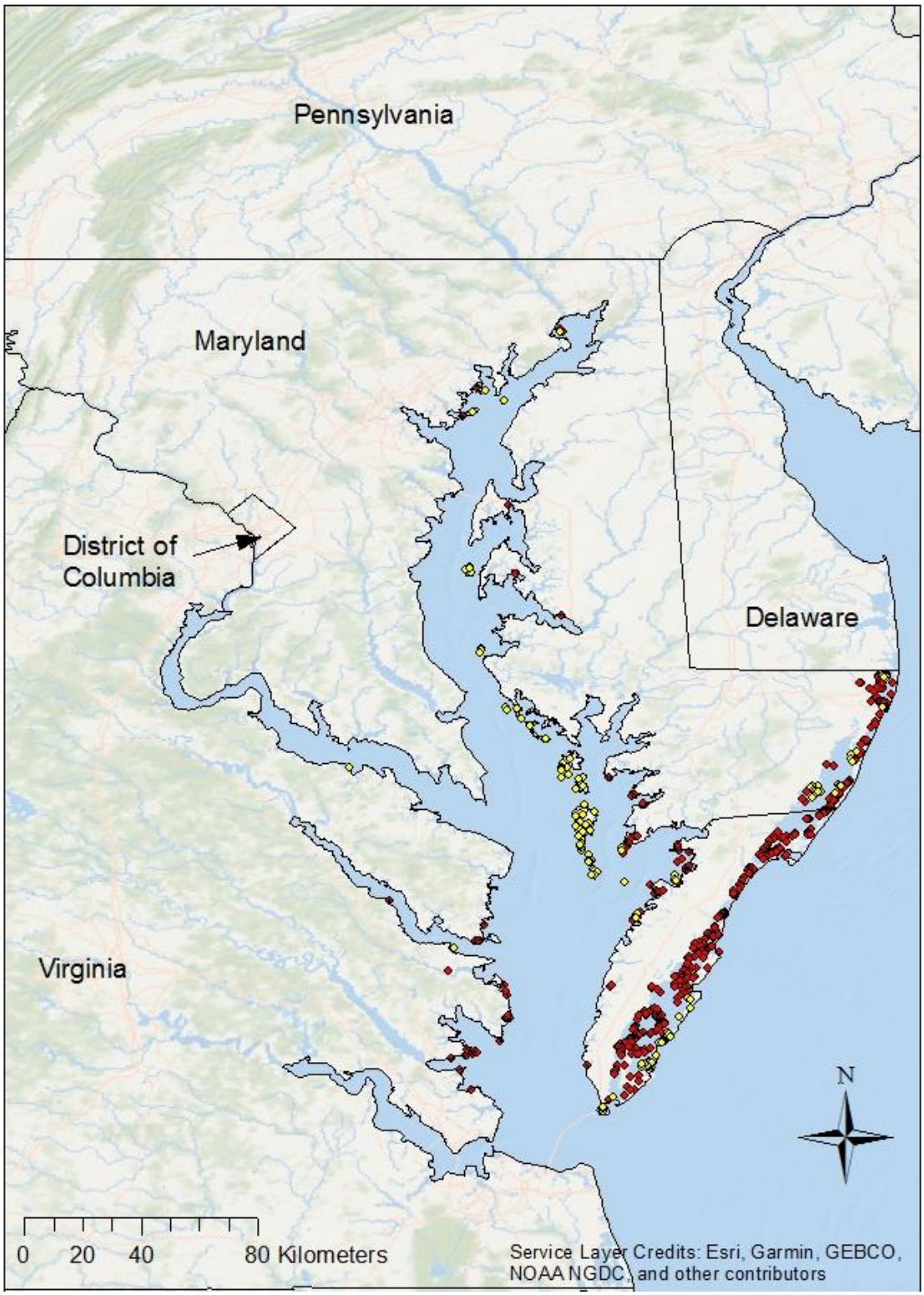

Figure 2B: Selected habitat islands within the Chesapeake Bay and Delmarva coastal bays of Maryland and Virginia. Yellow dots are islands included within the subset for area calculation and red dots are islands not included in area calculations. Subset islands were detected by the computer in the majority (>5) of study years.

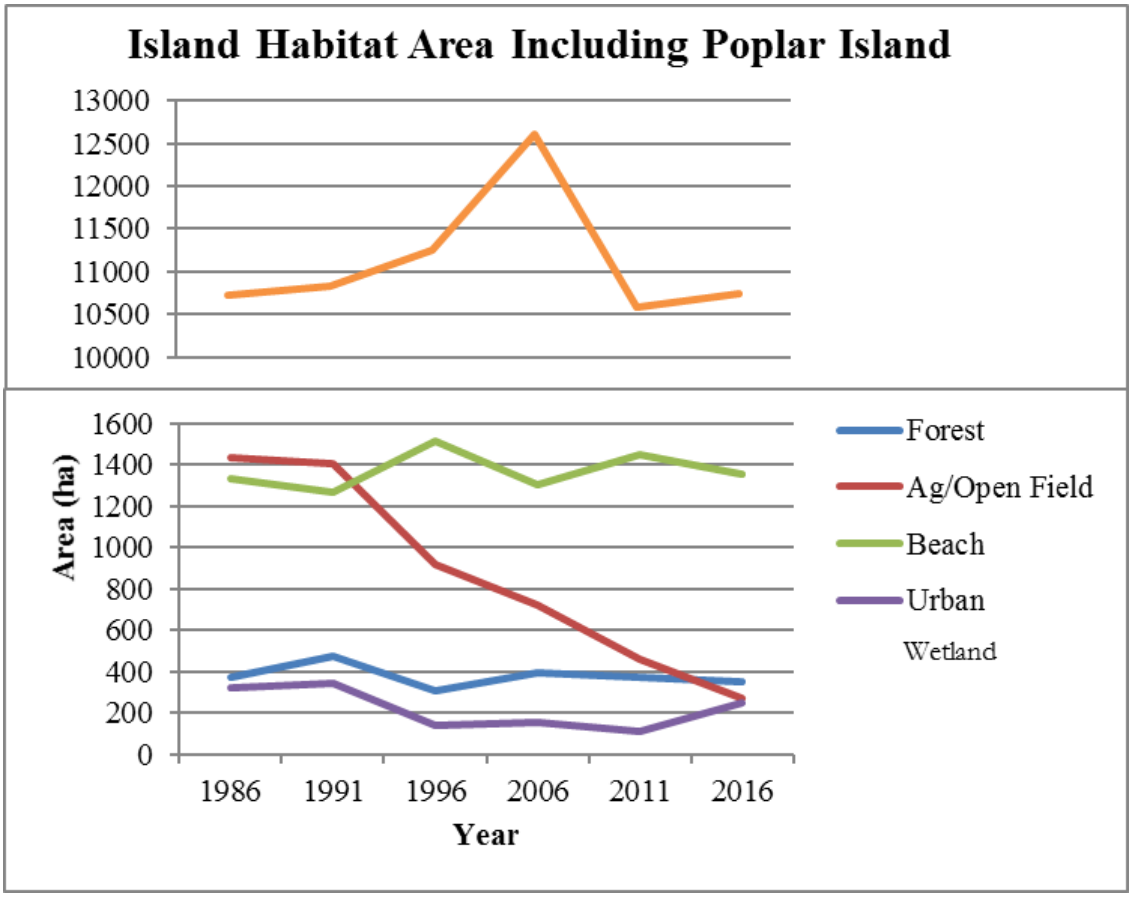

Figure 2C: Island habitat area in hectares from 1986 to 2016 for the Chesapeake Bay and coastal bays of Maryland and Virginia. The two peaks in beach habitat can be attributed to high amounts of sand accretion on coastal islands and the creation of the Paul S. Sarbanes Ecosystem Restoration Project at Poplar Island.

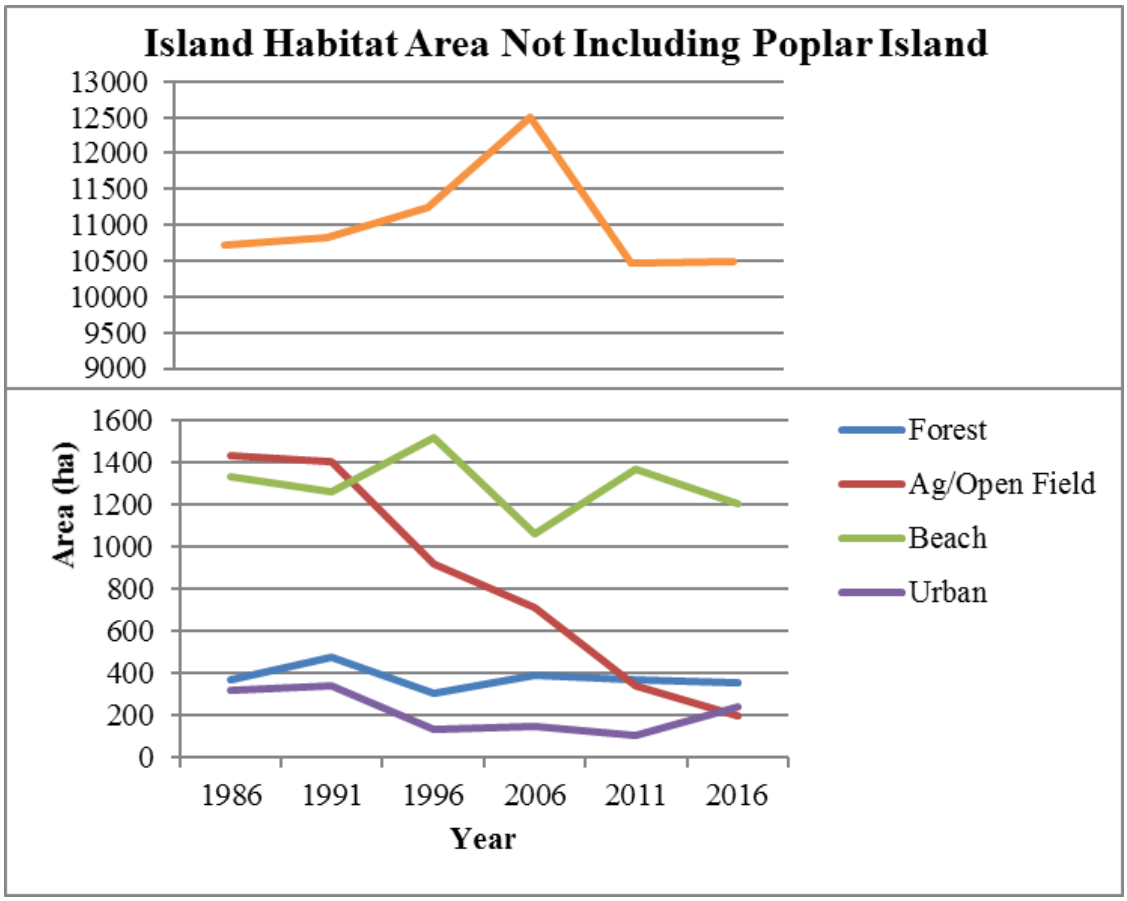

Figure 2D: Island habitat area in hectares from 1986 to 2016 for the Chesapeake Bay and coastal bays of Maryland and Virginia. The two peaks in beach habitat can be attributed to high amounts of sand accretion on coastal islands. The removal of Poplar Island from calculations caused a small decline in beach area but not a significant amount as originally expected.

Figure 3A: Map of all common tern (*Sterna hirundo*) breeding colonies in Maryland between 1986 and 2017. Nearly half (41.9%) of all colonies were located in Worchester county.

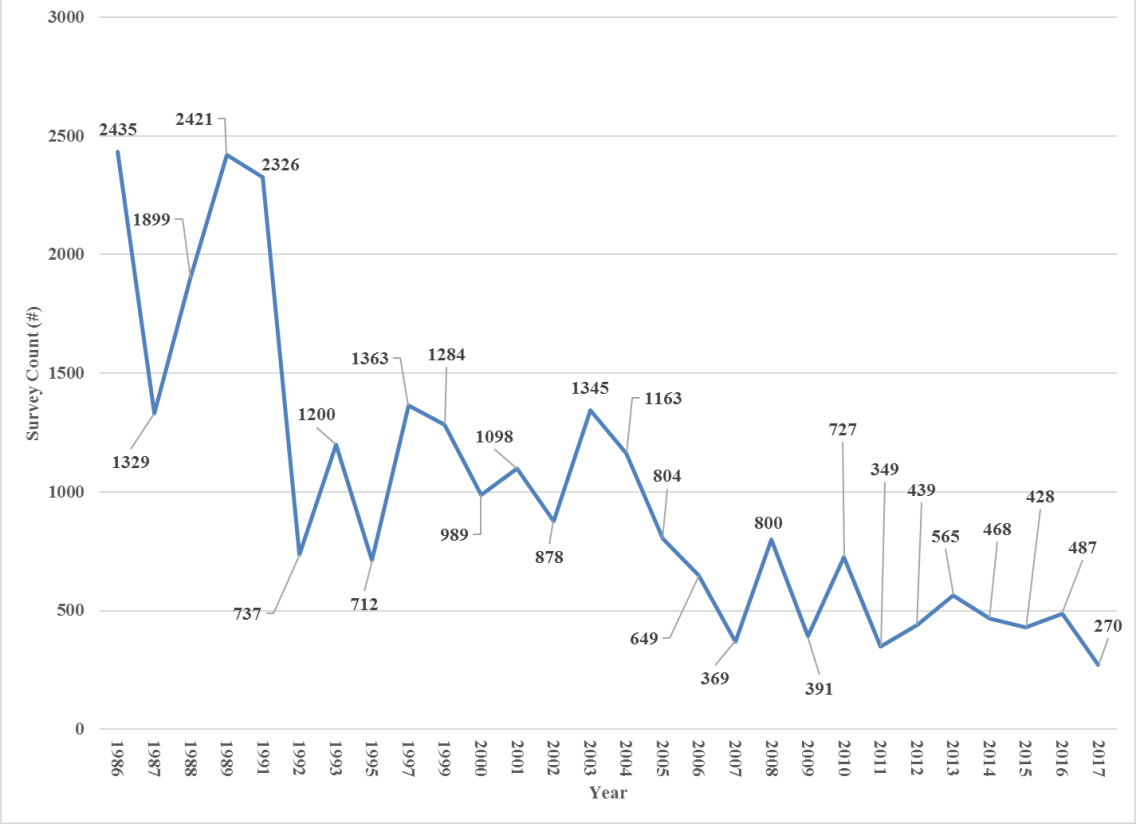

Figure 3B: Number of Maryland common tern (*Sterna hirundo*) breeding pairs from 1986 to 2017. Note that 1990, 1994, 1996, and 1998 were removed from all analyses due to incomplete sampling effort and are not included in this figure as a result. An overall decreasing trend in breeding pair numbers was observed over the study period.

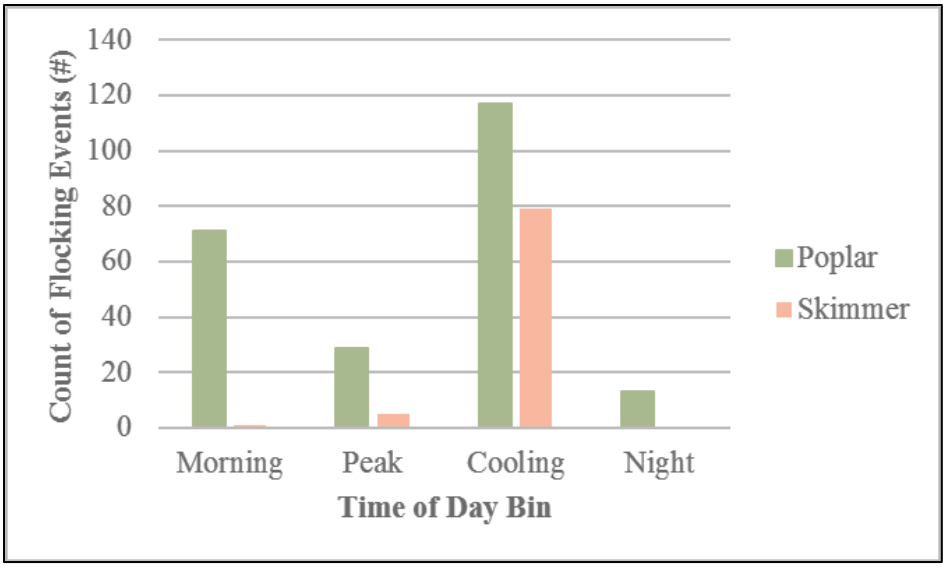

Figure 4A: Count of colony flocking events from review of colony camera footage gathered from Poplar and Skimmer Islands by time-of-day bins. At both colonies, poor IR illumination over the breeding colony prevented effective footage review between 2200 and 0400 nightly. Low counts on Skimmer Island were due to a significant loss of colony camera footage.

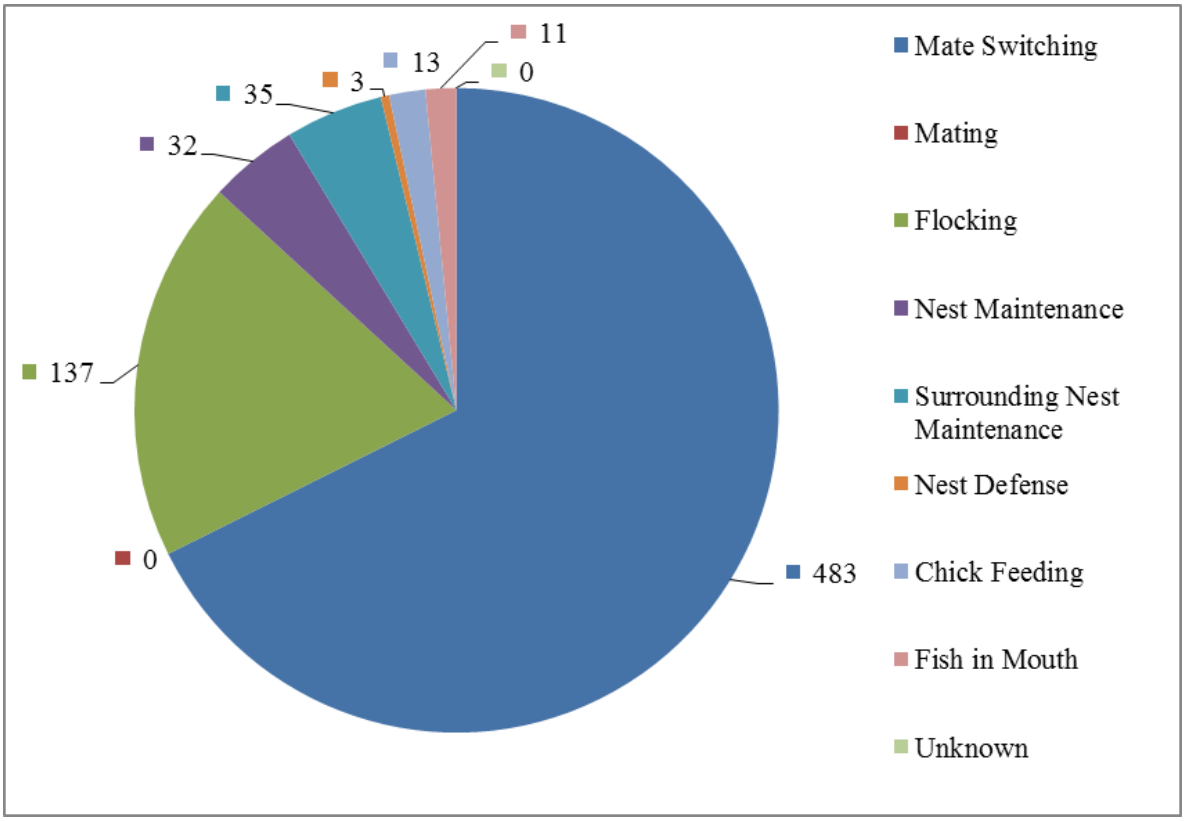

Figure 4B: Documented nesting behaviors at Poplar and Skimmer Islands, MD. Definitions of each behavior can be found within the Methods section. Counts from both colonies were combined since very few (<20) behavior events were documented on Skimmer Island over the course of the breeding season.

APPENDIX

Python script selecting all island pixels post-image classification within ArcMap 10.5. Running this script correctly creates a file with all land pixels which are completely enveloped by water pixels (i.e. islands). Comments are shown after "##".

```
>>> import arcpy
>>> arcpy.env.workspace = "C:/Users/…"   ##Set working directory to where the land-water mask unsimplified polygon file is located (see pg. 38).
>>> arcpy.env.overwriteOutput = True   ##Allow python to overwrite the output feature class if any changes are made.
>>> Outputfc = "HabitatIslands"   ##Name of the feature class containing all the island within the bay. This feature class may be given any name.
>>> Selection =
arcpy.SelectLayerByLocation_management("majclass_mfm8poly","INTERSECT", "majclass_mfm8poly selection", "50 meters", "NEW_SELECTION")   ##The script selects land polygons that intersect with water polygons and create a new selection. The first term in the parentheses is the mask polygon shapefile. "INTERSECT" is the layer selection criteria for the script. 50 meters was an arbitrary value since that is only used for "SEARCH_BY_DISTANCE" and other related queries. Adjusting this term does not alter accuracy of the script. "NEW SELECTION" ensures a new shapefile is created once the script is run.
>>> Selection =
arcpy.SelectLayerByAttribute_management("majclass_mfm8poly","REMOVE_FROM_SELECTION", ' "GRIDCODE" = 0 ')   ##Script only selects polygons that are coded as land (GRIDCODE =1) (i.e. islands) within the land-water mask polygon shapefile. All water polygons (GRIDCODE=0) are removed from the query.
>>> Selection =
arcpy.SelectLayerByAttribute_management("majclass_mfm8poly","REMOVE_FROM_SELECTION", ' "Area" < 2700 ')   ##From this new selection, the script selects islands that are greater than 1,800 sq. m (2 Landsat pixels). All islands smaller than this value are deleted from the query.
>>> arcpy.CopyFeatures_management("majclass_mfm8poly", "C:/Users/…")   ##Write the file path to where the queried island polygon will be saved. This file can then be uploaded into ArcMap 10.5 for further analysis.
```

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